Cross-sectional and time-series momentum on the JSE

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Abstract

This research report documents multiple accounts of past return-based momentum strategies employed on South African-listed equities over the period 2002.02-2015.05. Two cross-sectional momentum approaches – strategies that go long (short) in assets with relative formation period outperformance (underperformance) of peer stocks to make the winner (loser) portfolio – and four time-series approaches – strategies that go long (short) in assets with formation period outperformance (underperformance) of a hurdle rate to make the winner (loser) portfolio – are employed in this report.

This report finds that both the top decile winner portfolio and top half winner portfolio long-only cross-sectional momentum strategies outperform the benchmark. The 12-month formation period top decile winner achieves the highest long-only excess return of 30.21% per annum, whilst all the loser cross-sectional portfolios constitute a return-reducing funding portfolio when conducting an investment-neutral winner minus loser approach. Short-term zero investment exposure cross-sectional momentum strategies earn strong negative returns, thus presenting contrarian investment opportunities.

The two exposure-neutral winner minus loser time-series strategies exhibit similar results to the corresponding cross-sectional strategies, however the variable exposure strategies earn positive returns for every formation period – the 12-month formation period strategy being the best earner (25.92% p.a.). These variable exposure strategies earn time-varying returns from the market due to their non-zero net long market exposure as well as some residual return. This premium is left uncaptured by all investment-neutral approaches and is a strong cause of the lack of skewness of the variable exposure strategies' returns.

All of the examined exposure-neutral strategies exhibit significant leftward skewness due to two incidences of extreme and sustained drawdowns. Both incidences occur as a result of the momentum strategy holding market beta exposure of the opposite sign to the market's drastic turn; the first: positive exposure and market downturn, the second: negative exposure and positive upturn. These drawdowns are reduced when employing strategies of a more intermediate-term formation period such as the 12-month formation strategy.

This report's findings confirm the existence of cross-sectional and time-series momentum in South African-listed equities, as well as the case of equity momentum crashing. Further, it provides evidence for both explained and unexplained variations between the two types of momentum trading, with possibilities for further profitability when combining the two.

Declaration

I, Simon Lockhart-Ross, hereby declare that the work contained herein is my original work except where acknowledgments indicate otherwise. Neither the whole nor part of this report are being or have been submitted for another degree at this or any other university. The University of Cape Town is hereby empowered to reproduce this report, either wholly or partially, for research purposes in any manner whatsoever.

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1. Introduction

In its simplest form, a momentum strategy is a bet that past asset returns are a strong predictor of future asset returns. Until recently, two general forms of momentum trading strategies were widely-accepted amongst the mutual fund and academic bodies – both based on the relative strength of an asset's returns. Of the two, only cross-sectional momentum trading is of particular interest to this report while the moving average strategy is not. Moskowitz, Ooi and Pedersen (2012) deviated from these methods, forming a relatively new momentum trading method for consideration – time-series momentum.

Relative strength momentum approaches have historically produced significantly larger Sharpe ratios than passive market investments. However, according to Barroso and Santa-Clara (2012), cross-sectional approaches have also experienced the largest crashes when compared to other trading strategies. These inherent crashes have caused cross-sectional momentum to become unattractive to investors whom exhibit reasonable aversions to risk (Barroso and Santa-Clara, 2012). Trading strategies based on momentum as such have thus been called into question in markets with an ever-growing trend towards passive investments.

This report therefore aims to present a concise and accurate analysis of the performance of cross-sectional momentum trading strategies on South Africa's Johannesburg Securities Exchange (JSE). Given the commonly-found crash risk documented by Barroso and Santa-Clara (2012) and Daniel and Moskowitz (2013), this report will continue on to analyse the crash risk found in South Africa's equity momentum. The JSE is one such market yet to be documented for momentum crashes; a key justification for this study.

In addition, this report presents an analysis of Moskowitz et al's (2012) time-series momentum on the JSE, to provide comparability of profitability and crash risk with the corresponding cross-sectional approaches. Little emphasis has been placed on this time-series momentum trading given its relatively new-found profitability. Again, this form of momentum trading has not been documented in the South African context, and has not been directly examined for crash risk on a global front.

The remainder of this report is organised as follows: Chapter 2 presents a review of international and South African literature related to cross-sectional momentum strategies. Following this, a review of international literature related to various aspects of time-series momentum is presented. The remainder of the chapter presents a review of international literature on the inherent momentum crash characteristic of cross-sectional strategies, and how such risk may be reduced.

Chapter 3 presents an analysis and discussion of the data used in this study. The research methods employed in this report are then detailed through the remainder of the chapter. Results of the report are presented in chapter 4, followed by a discussion of said results. Chapter 5 draws conclusions from the results, before final comments about the study are made.

2. A review of prior research

This chapter presents a review of international and South African literature related to momentum in common shares. The chapter is divided into three primary categories: Cross-sectional momentum, time-series momentum, and momentum crashes.

2.1. A review of prior research related to cross-sectional momentum

Cross-sectional momentum strategies compare an asset's returns over a particular period to returns of peer assets over the same period. Jegadeesh and Titman's (1993) study is considered to be the first documented report of cross-sectional momentum strategies on common shares' returns in the United States of America (US). Jegadeesh and Titman (1993) constructed their study so as to reconcile academic literature with market constituents' use of relative strength approaches – a strong deviation from the then hot topic of contrarian investment strategies. The aim of their study, as with the first aim of this study, was to investigate whether their 'buying past winners and selling past losers' strategy could generate returns in excess of a benchmark. Both a buy-and-hold technique and a monthly rebalanced, equally-weighted technique were employed to examine the strategies' profitability.

Jegadeesh and Titman (1993) employed 16 cross-sectional strategies, varying both the length of the formation period and the length of the subsequent holding period. The formation period and holding period were varied independently, from one quarter (3-month period) to four quarters (12-month period) of returns. The following strategy matrix reflects these variations of the quarterly formation and holding periods, respectively:

(1x1)	(1x2)	(1x3)	(1x4)
(2x1)	(2x2)	(2x3)	(2x4)
(3x1)	(3x2)	(3x3)	(3x4)
(4x1)	(4x2)	(4x3)	(4x4).

Henceforth this report will document all trading strategies in the general form of *J*x*K*, where the first number represents the formation period in months, and the second number represents the holding period in months.

A second set of Jegadeesh and Titman's (1993) strategies was employed (totalling 32 strategies in all), differing only in that a 1-week period was left unexamined between the formation period and subsequent holding period. This week-long gap served as a robustness test so as to avoid asset pricing issues relating to bid-ask spreads, price pressure, and lagged reaction effects as described in Jegadeesh and Titman's (1993) study.

At the beginning of each month *t,* all shares in the sample were ascendingly ranked according to their return over the formation period of *J*-months. Decile portfolios were then formed where the highest ranked portfolio corresponded with the highest ranked decile of shares, through to the lowest decile portfolio which contained the lowest ranked decile of shares in the sample. Shares contained in each of the decile portfolios were equally-weighted for ease of calculation. Jegadeesh and Titman (1993) described the winner portfolio based on its constituent shares' relative outperformance of its peers over the formation period, and the loser portfolio based on its constituent shares' relative underperformance of its peers over the same formation period.

Post share-ranking and portfolio-construction*,* Jegadeesh and Titman's (1993) strategy bought the winner portfolio and shorted the loser portfolio to establish a zero net investment position of winner minus loser (WML) portfolio. These positions were held for the duration of the holding period of *K*-months, before the positions were closed. For holding periods of greater than 1-month (all holding periods by Jegadeesh and Titman's (1993) design), overlapping portfolios were used. Thus in any given month *t*, a series of winner and loser portfolios was held with 0-months (holding period expired at *t*) to 12-months (four-quarter holding period formed at *t*) remaining of their holding period.

Jegadeesh and Titman (1993) found that using daily returns data from the Center for Research in Securities Prices (CSRP) File Indices, over the period 1965 to 1989, all WML portfolio returns per dollar long in the portfolio were positive. All 32 strategies reported statistically significant positive returns with the exception of the 3x3 WML portfolio without the 1-week gap. They also found that the most successful WML portfolio strategy ranked shares according to their 12-month formation period, and held these positions for a 3-month period i.e. 12x3. These strategies thereby yielded 1.31% and 1.49% per month for the strategies excluding and including the 1-week gap, respectively.

Jegadeesh and Titman (1993) went on to test the profitability of the 6x6 WML strategy over a long-term horizon. They found that, as before, positive returns throughout year one (with the exception of the first month) were achieved. The average returns achieved over the second and third years were negative and statistically zero, respectively. As such, Jegadeesh and Titman (1993) concluded that the strategy employed did not select shares with unconditional outperformance, and as such the outperformance achieved over the first year was likely to be temporary. Jegadeesh and Titman (1993) thus proposed that the trend may be a result of market constituents applying WML portfolio strategies. This application thereby temporarily drove share prices away from their long-term means – thus causing an overreaction to past performance. They also acknowledged that this temporary overreaction was reversed over the longer-term.

Whilst numerous reports covering many equities markets have been published on cross-sectional momentum, little has changed in the way of methodology and approach. As such, the relevance of Jegadeesh and Titman's (1993) work to this report is more highly valued than the masses of similar research in the field.

2.2. A REVIEW OF PRIOR RESEARCH RELATED TO TIME-SERIES MOMENTUM

Prior to Jegadeesh and Titman's (1993) examination of cross-sectional momentum strategies' outperformance, Grinblatt and Titman (1989, 1993) examined a selection of US mutual funds' quarterly performance. They identified a general inclination of the sample funds to buy shares that had appreciated in price over the prior quarter. Jegadeesh and Titman (1993) attributed this to the share's relative strength in the prior quarter. However, they did not identify the peer shares to which the relative strength was determined, nor did they provide evidence of the funds' use of moving average approaches. As such, this inclination to buy appreciating shares may well be the first documented case of what is now known as time-series momentum.

In contrast to relative strength strategies, time-series momentum trading is 'absolute excess return' based as opposed to relative excess return based. A time-series momentum trading strategy simply establishes a position of exposure to an asset based on its own formation period's excess return (Moskowitz et al, 2012). Time-series momentum (or absolute momentum) trading is thus a trend-following technique by definition. Post-Fama's (1970) efficient markets hypothesis, trend-following techniques were deemed inconsequential. However, Antonacci (2014) wrote that methods employed to profit from securities trends are becoming of greater importance to the academic universe due to their robustness across time and asset class.

Moskowitz et al (2012) documented a multi-asset time-series momentum trading approach to determine the strength of assets' future return predictability. Moskowitz et al (2012) examined the approach on 58 liquid instruments over a 25-year sample of data. Where Jegadeesh and Titman's (1993) cross-sectional strategies employed an overlapping portfolio structure for holding periods of greater than 1-month, Moskowitz et al (2012) employed a set of single time-series returns without overlapping. Jegadeesh and Titman's (1993) structure accounts for investment realism where investors are able to enter the strategy at any month over the sample. Moskowitz et al's (2012) structure lacks this element, but due to the non-overlapping structure, return data was not reused in multiple portfolios over the same time period. As such, Moskowitz et al's (2012) structure likely reduced the potential for data mining biases. Ultimately these considerations are inconsequential to this report given the scope being limited to 1-month holding periods.

Moskowitz et al (2012) divided up their methodology between two approaches – a regression analysis to determine the instruments' price continuation, and a simulation of the momentum strategies in a fashion similar to Jegadeesh and Titman's (1993) study. For the regression analysis, Moskowitz et al (2012) regressed the excess return (return of the instrument in excess of the risk-free rate, r^s_t) of each instrument *s* in month *t,* on its *h*-months lagged excess return r^s_{t-h}. Both r^s_t and r^s_{t-h} were divided by their respective ex-ante volatility estimates σ^s_{t-1} to achieve comparability across all of the examined instruments, and ease of aggregation. Running regressions with lags of h = 1, 2, … 60 months, the regression equation fit the form:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \frac{\beta_h r_{t-h}^s}{\sigma_{t-h-1}^s} + \varepsilon_t^s.$$

Considering the trading strategies employed in Moskowitz et al's (2012) study, a second regression specification was also constructed. This specification focused on the positive or negative sign of the lagged return, as this is ultimately the core determinant of an instruments' return continuation. If return continuation is apparent, positive (negative) lagged excess return implies positive (negative) future excess returns. If return continuation is absent, positive (negative) lagged excess return implies negative (positive) future excess returns. The second regression specification fit the form:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + \varepsilon_t^s.$$

Moskowitz et al (2012) found that the two regression specifications yielded similar results for the pooled instrument sample and for each instrument independently. Both specifications displayed strong return continuations for lags of 1-month to 12-months, with weak return reversals over the following four years. These results are consistent with Jegadeesh and Titman's (1993) findings for cross-sectional momentum.

The second approach taken by Moskowitz et al (2012) involved a variable formation period and holding period time-series portfolio simulation. In comparison to the simulation conducted by Jegadeesh and Titman (1993), Moskowitz et al's (2012) strategy matrix of monthly formation and holding periods, was constructed as follows:

(1x1)	(1x3)	(1x6)	(1x9)	(1x12)	(1x24)	(1x36)	(1x48)
(3x1)	(3x3)	(3x6)	(3x9)	(3x12)	(3x24)	(3x36)	(3x48)
(6x1)	(6x3)	(6x6)	(6x9)	(6x12)	(6x24)	(6x36)	(6x48)
(9x1)	(9x3)	(9x6)	(9x9)	(9x12)	(9x24)	(9x36)	(9x48)
(12x1)	(12x3)	(12x6)	(12x9)	(12x12)	(12x24)	(12x36)	(12x48)
(24x1)	(24x3)	(24x6)	(24x9)	(24x12)	(24x24)	(24x36)	(24x48)
(36x1)	(36x3)	(36x6)	(36x9)	(36x12)	(36x24)	(36x36)	(36x48)
(48x1)	(48x3)	(48x6)	(48x9)	(48x12)	(48x24)	(48x36)	(48x48).

Moskowitz et al's (2012) matrix construction allowed for an examination of both short-term (<= 12 months) and long-term (> 12 months) asset trends, where Jegadeesh and Titman (1993) examined only short-term. This construction also maintains some alignment with the return time frame over which Moskowitz et al (2012) introduced their regression analysis.

In the approach, instruments were selected for portfolios by Moskowitz et al (2012) on the basis of their excess returns. As before, all excess returns were scaled by their corresponding ex-ante volatility estimate. The volatility scaling ensured "that the strategy was not dominated by a few volatile periods"

(Moskowitz et al, 2012). Any instrument that exhibited positive excess returns over the formation period was bought (winner portfolio), with the remainder being shorted (loser portfolio). This time-series approach bears vast contrast to the cross-sectional approach in its threshold for asset sales and purchases. Goyal and Jegadeesh (2015) noted this as a key difference between the two methodologies' profitability, as the time-series approach implements a fixed threshold of zero excess returns as opposed to cross-sectional's variable threshold. An interesting point for investigation would be the effect of different thresholds for asset selection – absolute cut-offs for time-series momentum and relative cut-offs for cross-sectional momentum– on the returns to momentum strategies; something to be considered later in this report (see sub-chapters 4.1. and 4.2.).

Goyal and Jegadeesh (2015) examined a generic set of strategies to emphasise this asset allocation issue. For the cross-sectional momentum component, shares with excess returns exceeding the cross-sectional average of all the shares in the sample were bought, with the remaining shares being sold. The time-series momentum component was conducted as in Moskowitz et al's (2012) work. Goyal and Jegadeesh (2015) thus emphasised that in times of large (small) cross-sectional average excess returns, a significant number of shares with positive (negative) excess returns – but not exceeding the cross-sectional average – would be shorted (bought). Thus the cross-sectional approach established short (long) positions in shares where the time-series approach established long (short) positions.

The profitability of the two approaches can therefore be substantially different. Goyal and Jegadeesh (2015) refer to this specific deviation as a general asset selection difference, or differences due to 'stock selection'. Jegadeesh and Titman's (1993) decile application of the WML portfolio is likely to reduce this effect to an extent, as only those shares with significantly extreme outperformance or underperformance of the cross-sectional average were selected for portfolios. This however introduces a separate asset selection issue as time-series strategies utilise all shares as longs or shorts.

Moskowitz et al (2012) found that the past 12-month excess returns of each of the 58 instruments examined were positive predictors of that instrument's future returns. Similar to their findings from the regression analysis, return continuation from time-series momentum was apparent over a holding period of 1-month to 12-months, with reversals occurring thereafter. Additionally, Moskowitz et al (2012) found that time-series momentum outperformance exhibited little correlation to the equity buy-and-hold benchmark alternative, and equally low correlation to standard asset pricing factors. This poses a curious question about asset pricing models; something to be considered in future research.

Moskowitz et al (2012) also found that time-series momentum strategies outperformed the benchmark most significantly when the equity market experienced large movements – including tail events. The time-series momentum profits exhibited straddle-like option strategy payoffs, with large returns earned from significant equity market volatility. As such, Moskowitz et al (2012) deemed that time-series momentum outperformance cannot be considered compensation for equity market crash risk (downside events) nor compensation for tail events (extreme probability events).

Finally, Moskowitz et al (2012) presented an alternative comparison of time-series and cross-sectional momentum methods. By regressing the excess returns obtained from the time-series momentum strategy (independent variable) on the excess returns obtained from the corresponding cross-sectional momentum strategy (dependent variable), Moskowitz et al (2012) found that the intercept term was insignificant. Exchanging the independent and dependent variables, Moskowitz et al (2012) found that the intercept term was significantly positive. As such, they conclude that time-series momentum was not fully explained by cross-sectional momentum over the sample, but that cross-sectional momentum was fully explained by time-series momentum.

Goyal and Jegadeesh (2015) re-examined the comparison drawn by Moskowitz et al (2012). Goyal and Jegadeesh (2015) conducted their study on non-micro market capitalisation shares listed on the New York Stock Exchange (NYSE) over the period of 1946 to 2013. For comparability, Goyal and Jegadeesh (2015) examined individual stocks as opposed to stock futures (Moskowitz et al (2012)) and stock indices, thus continuing in-line with the majority of return predictability literature. Furthermore, they questioned the external validity of studies conducted on instruments other than individual stocks.

Unlike Moskowitz et al (2012), Goyal and Jegadeesh (2015) implemented an overlapping structure for holding periods of greater than 1-month. The following strategy matrix was employed in their study:

(1x1)	(1x3)	(1x6)	(1x12)	(1x36)	(1x60)
(3x1)	(3x3)	(3x6)	(3x12)	(3x36)	(3x60)
(6x1)	(6x3)	(6x6)	(6x12)	(6x36)	(6x60)
(12x1)	(12x3)	(12x6)	(12x12)	(12x36)	(12x60)
(36x1)	(36x3)	(36x6)	(36x12)	(36x36)	(36x60)
(60x1)	(60x3)	(60x6)	(60x12)	(60x36)	(60x60).

Goyal and Jegadeesh (2015) found that all time-series momentum strategies tested earned positive excess returns, including the 1x1 strategy for which Jegadeesh and Titman (1993) found negative returns. Where Moskowitz et al (2012) found evidence of long-term return reversals, Goyal and Jegadeesh (2015) concluded that past stock returns were positive predictors of future stock returns over both the short-term and long-term horizon. The evidence was robust over short-term and long-term formation periods, as well as short-term and long-term holding periods. Additionally, every time-series strategy examined earned returns in excess of the corresponding cross-sectional strategy. Goyal and Jegadeesh (2015) also confirmed Jegadeesh and Titman's (1993) findings with evidence of the 6x6 cross-sectional strategy yielding significantly positive excess returns.

The analysis identified two further differences between the approaches and aptly labelled them as a 'risk premium' and a 'market timing' difference. Time-series strategies, in general, invest one unit of currency (one US dollar in Goyal and Jegadeesh's paper (2015) and one South African rand in this report) long when the asset generates returns in excess of the risk-free rate, and one unit of currency short otherwise. In months where more (less) than half of the assets generate positive formation excess returns, the WML strategy experiences a net long (short) investment.

Additionally, Goyal and Jegadeesh (2015) described that if the average risk premium earned by constituent assets over the sample is positive (negative), then the average net investment for that sample is long (short). Thus the time-series approach earns the average risk premium over the sample. Cross-sectional approaches on the other hand experience zero net investment by design, and thus earn no such risk premium. Goyal and Jegadeesh's (2015) market timing component exists because, in general, a larger number of assets generate positive (negative) excess returns in the wake of a market up-trend (down-trend). As such, the time-series approach experiences a large net long (short) investment in up-trending (down-trending) market conditions – a clear market timing scenario.

Over their sample, all differences between Goyal and Jegadeesh's (2015) time-series and cross-sectional strategies were completely explained by the market timing and risk premium components, collectively. Although significant over all formation periods, the risk premium component increased in magnitude and significance with longer formation periods. In contrast, the market timing element was only significant for 1-month holding periods, whilst the stock selection component was not significant for any tested formation period other than the 1x1 strategy.

Finally, following Moskowitz et al's (2012) alternative comparison, Goyal and Jegadeesh (2015) conducted regressions with their time-series momentum and cross-sectional momentum strategies to observe whether one explains the other. Regressing with time-series momentum returns as the dependent variable, Goyal and Jegadeesh (2015) observed significantly positive intercepts over both long-term and short-term periods. However, regressing with cross-sectional momentum returns as the dependent variable, the results proved inconclusive. As such, Goyal and Jegadeesh (2015) rebutted Moskowitz et al (2012) and concluded that time-series momentum did not fully explain cross-sectional momentum over the sample of individual equities.

Dudler, Gmuer and Malamud (2014) continued with Moskowitz et al's (2012) study on time-series momentum, examining the effect of risk-adjustment on the strategies' profitability. Having selected 64 futures contracts linked to stock indices, commodities, bonds, interest rates and currencies, Dudler et al's (2014) method differed from Moskowitz et al's (2012) in its normalisation of past returns. Where Moskowitz et al (2012) normalised all returns by their respective ex-ante price volatility estimates, Dudler et al (2014) normalised past returns by their exponentially-weighted, lagged moving average of realised momentum returns volatility.

Additionally, Dudler et al (2014) described the use of monthly trading strategies by Moskowitz et al (2012) as inefficient as the time-delay restricts investors' ability to take well-timed positions in instruments when new information arises. However, Dudler et al (2014) found that the use of risk-adjusted time-series momentum halved the number of transactions of that required by the corresponding unadjusted strategy. As such, some improvement of the Sharpe ratio was attributed to reduced transaction costs associated with the strategy.

Finally, Dudler et al (2014) identified that their risk-adjusted time-series momentum strategies outperformed the corresponding unadjusted strategies. A Sharpe ratio outperformance of 10% to 15% on average was consistent for a large majority of formation and holding periods over their 30-year sample spanning January 1984 to January 2014. They added that the outperformance was especially large for very long-term strategies.

The findings of the aforementioned studies on momentum have interesting implications for market efficiency. Evidence of momentum strategy portfolio outperformance, as seen throughout this chapter would strongly question the market efficiency of the JSE. However, Fama's (1991) joint hypothesis problem makes such outperformance an unlikely disproval of the weak-form of market efficiency described by Fama (1970). Though, given that the focus of this report surrounds momentum crashes rather than market efficiency, implications about the JSE's market efficiency are not explicitly made.

2.3. A REVIEW OF PRIOR RESEARCH RELATED TO MOMENTUM CRASHES

Whilst Jegadeesh and Titman's (1993) study's key focus area was the application of cross-sectional momentum strategies, they identified an interesting risk characteristic of the approach. Over their data sample, they investigated the average betas of their 6x6 winner and loser portfolios in comparison to the average beta of the full sample. They found that both the winner and loser portfolios exhibited higher betas on average than the average beta of the whole sample for each period, thus implying higher than average risk for both portfolios.

Additionally, they found that the winner portfolio generated betas marginally greater than the loser portfolio on average, thus the WML maintained a beta marginally different from zero. As such the returns achieved by the approach were arguably unrelated to sample market conditions. This finding demonstrates that cross-sectional momentum strategies should produce profits irrespective of market returns.

However, Daniel and Moskowitz (2013) found that returns to cross-sectional momentum strategies were robustly negatively skewed. As such, traders of such strategies often experienced sporadic but sustained and significantly large negative tail events over the sample. Daniel and Moskowitz (2013) termed these events momentum crashes. Having employed a 12x1 WML similar to Jegadeesh and Titman (1993), their 1927 to 2013 CRSP US equity sample returned two sustained crash periods – June 1932 to December 1939, and March 2009 to March 2013.

In total, the worst 15 momentum returns (crashes) over Daniel and Moskowitz's (2013) sample exhibited monthly losses between 24.04% and 74.36%. However, Daniel and Moskowitz (2013) identified that the worst 14 of the 15 crash events occurred in months when the market recovered dramatically from a down-trend over the prior two years. All 15 events arose following the same down-trend. Additionally, Daniel and Moskowitz (2013) identified that crash losses were incurred over multiple months thereby indicating their sustained impact over relatively extended time periods.

Finally, and most importantly, Daniel and Moskowitz (2013) identified that the crash events in their sample occurred solely as a result of the loser portfolio's strong performance relative to the winner portfolio. This point is stressed by both Daniel and Moskowitz's (2013) and Barroso and Santa-Clara's (2012) studies. Over July and August of 1932 the US market rose 86%, however the WML portfolio returned -206%. This was purely a result of the long winner portfolio (up 30%) underperforming the short loser portfolio (up 236%) by a drastic margin. Barroso and Santa-Clara (2012) quote a similar styled crash of 73.42% loss over three months in 2009. Clearly, the crash events are incidences of the short portfolio "crashing up" (Daniel and Moskowitz, 2013) over the long portfolio.

Daniel and Moskowitz (2013) added to Jegadeesh and Titman's (1993) findings regarding momentum strategy betas to attempt to explain the observed momentum crashes. Over the sample period, Daniel and Moskowitz (2013) found that the 6-month rolling betas of the winner and loser portfolios individually varied over time. The loser portfolio's beta tended to rise substantially above the winner portfolio's beta in volatile and down-trending market conditions such as those observed immediately preceding the crash months. Logically this is the case: in times of market contraction, high beta stocks (those affected most severely by market downturns) would underperform and therefore be considered for the loser portfolio, whilst low beta stocks (those affected least by market downturns) would outperform and thus be considered for the winner portfolio.

This finding implied that the loser portfolio was more significantly exposed to market movements than was the winner portfolio when moving into crash periods. As such, the rapid and substantial market turnaround – following the market down-trend – generated significantly positive returns to the loser portfolio but significantly less positive returns to the winner portfolio. Thus, the significantly negative beta WML strategy generated significant losses: momentum crashes. As such, Jegadeesh and Titman's (1993) finding that momentum profits exist across all market conditions is inaccurate.

Daniel and Moskowitz (2013) thus advocated the use of a market-hedged cross-sectional momentum strategy, similar to that discussed by Grundy and Martin (2001). Grundy and Martin (2001) implemented a momentum portfolio strategy with both size-neutral and market-neutral exposures. They found that these hedges resulted in both high momentum returns and high Sharpe ratios over the period prior to World War II in which the unhedged strategy performed poorly.

However, Daniel and Moskowitz (2013) posed that Grundy and Martin's (2001) use of ex-post beta estimates rather than ex-ante beta estimates resulted in significantly upward-biased performance indicators. To reduce look-ahead bias, Daniel and Moskowitz (2013) implemented a purely ex-ante market-neutral and size-neutral momentum strategy as opposed to Grundy and Martin's (2001) ex-post strategy. They found that the ex-ante hedges did not mitigate the momentum crashes and actually resulted in poorer performance than the originally unhedged momentum portfolio. As such, this hedging technique is ignored here forth.

Daniel and Moskowitz (2013) promoted a second style of momentum hedging, more prevalent in Barroso and Santa-Clara's (2012) paper. Instead of a zero exposure strategy, Barroso and Santa-Clara (2012) employed a return-scaled strategy to establish a constant risk portfolio across time. For each month, an ex-ante momentum variance estimate was calculated using daily returns over the prior six months. Weights in the long and short portfolios to achieve the WML portfolio were then scaled by the square root of the variance estimate (volatility estimate) to achieve a target annualised volatility of 12%. The selection criterion for the 12% per annum target was not disclosed.

Daniel and Moskowitz (2013) employed a similar risk-adjusted WML portfolio on non-US data. However, Daniel and Moskowitz's (2013) variance estimates were calculated ex-post over the whole sample period. As with Grundy and Martin (2001), a large element of upward-bias existed in the performance of their risk-adjusted WML portfolio, in addition to the strong look-ahead bias. As such, only Barroso and Santa-Clara's (2012) risk-adjustment is emphasised below.

Barroso and Santa-Clara (2012) found that the risk-hedged momentum strategy achieved cumulative returns almost 90 times larger than the vanilla WML portfolio strategy over the 1927 to 2011 sample. The resulting Sharpe ratio of the risk-managed WML portfolio nearly doubled that of the vanilla strategy due to significantly larger average returns and significantly lower risk. Finally, Barroso and Santa-Clara (2012) found that the vanilla WML portfolio exhibited excess kurtosis of 18.24 and skewness of -2.47 over the sample. In comparison, the risk-managed WML portfolio exhibited excess kurtosis and skewness of 2.68 and -0.42, respectively. As such, Barroso and Santa-Clara (2012) concluded that the employment of a volatility-targeting, hedged momentum strategy mitigated the risk of momentum crashing in its entirety.

Han, Zhou and Zhu (2014) proposed another alternative to momentum crash mitigation. As opposed to those above, Han et al (2014) relaxed the requirement that all positions in stocks must be held from the beginning to the end of the specified holding period. Without this relaxed assumption, their suggested stop-loss strategy for crash mitigation is not possible in other studies. Han et al (2014) identified that a large majority of professional investors employ some form of stop-loss strategy to mitigate significant losses, and as such used this as a justification for their method. Han et al (2014) formed 6x1 WML decile portfolios of equally-weighted stocks from daily and monthly stock data from the January 1926 to December 2011 CRSP file.

Over the 15 months where Daniel and Moskowitz (2013) found momentum losses exceeding 20%, Han et al (2014) found that the use of a 10% stop-loss strategy limited the maximum loss to 9.07%. Loss levels of 5% and 15% were also tested for robustness. The stop-loss technique even resulted in positive returns for three of the worst months (2.75%, 8.16% and 2.53%) as opposed to the original losses (-49.79%, -20.45% and -39.43%). Additionally, over Daniel and Moskowitz's (2013) identified crash periods, the 10% stop-loss drastically improved cumulative returns (-70.24%, -54.06%, and -39.52% to 10.91%, 16.16%, and -11.82%). As such, the stop-loss approach not only calmed the three crashes, but resulted in significant profits in two of the three original crash periods.

Moskowitz et al's (2012) study on time-series momentum briefly revealed a similar momentum crash to that of cross-sectional approaches. They documented that their time-series momentum strategy (see sub-chapter 2.2) earned large profits over the final quarter of 2008 when equity market prices fell sharply. When the recent economic crisis stabilised over 2009, the strategy suffered significant losses. Similar to the cross-sectional crashes discussed by Daniel and Moskowitz (2013) and Barroso and Santa-Clara (2012), Moskowitz et al's (2012) time-series momentum crash occurred over a period where equity markets recovered substantially following a period of down-trending equities prices. It is therefore unlikely that time-series momentum presents any significant momentum crash risk mitigation possibilities in US stocks considering that the strategy exhibits similar characteristics to the cross-sectional momentum strategy itself.

Whilst cross-sectional momentum strategies have been examined on numerous occasions globally, the investigation of crash risk attributed to such approaches is relatively understudied. This report draws attention to the fact that no South African literature related to momentum crashes on the JSE exists. Additionally, time-series momentum represents new ground for documentation in South African equities. Finally, to date, momentum crashes have only been directly tested on cross-sectional strategies with a hint of focus placed on time-series strategies.

Considering the full scope discussed over this chapter, the profitability of both cross-sectional and time-series momentum trading strategies on the JSE is presented throughout the remainder of this report. Particular attention is drawn to the crash characteristic of these approaches. Chapter 3, to follow, describes the research methods employed in this report, as well as the data employed for these methods.

3. Data and research methods

This chapter describes the data on which research was conducted for the compilation of this report. Additionally, this chapter goes on to outline the research methods employed for this study as aligned with the literature in chapter 2.

3.1. Data – Johannesburg Securities Exchange

For the period February 2002 to May 2015, monthly total returns for the most liquidly-traded 170 JSE-listed stocks (by market capitalisation as at the last close of May 2015) were obtained from Bloomberg's database. The period was selected to fall in-time with the initiation of the chosen benchmark as well as incorporating the latest available data at initiation of this report. The descriptive statistics of each momentum portfolio are shown in chapter 4 under the appropriate sub-chapter. Panel A of Table 3.1. presents the descriptive statistics of the chosen benchmark, South Africa's Shareholder-weighted All-Share Index (SWIX ALSI) Panel B presents the descriptive statistics of the 'hurdle return rate', South Africa's R186 bond yield, and Panel C presents the descriptive statistics of the equally-weighted index of stocks in the sample.

Table 3.1.: Benchmark return characteristics, 2002.02-2015.05

This table presents the characteristics of the monthly Shareholder-weighted All-Share index (SWIX ALSI) excess returns, the equally-weighted index (EW Index) excess returns, and the hurdle return (r_f) over the period 2002.02-2015.05. The mean returns and standard deviations are in percent and annualised, whilst the Sharpe ratio is also annualised.

Panel A	SWIX ALSI	Panel B	'Hurdle Return'	Panel C	EW Index
Excess return, $R_{SWIX\ ALSI}$	10.30	**Return, r_f**	8.08	**Excess return, $R_{EW\ Index}$**	16.26
Standard deviation, $\sigma_{SWIX\ ALSI}$	15.17	**Standard deviation, σ_{rf}**	0.22	**Standard deviation, $\sigma_{EW\ Index}$**	13.13
Skew, $SK_{SWIX\ ALSI}$	-0.33	**Skew, SK_{rf}**	1.03	**Skew, $SK_{EW\ Index}$**	-0.55
Sharpe ratio, $SR_{SWIX\ ALSI}$	0.68	**Sharpe ratio, SR_{rf}**	-	**Sharpe ratio, $SR_{EW\ Index}$**	1.24

3.1.1. Data justifications and adjustments

In order to maintain a strong South African reference point, this report references the SWIX ALSI as its benchmark for returns. The SWIX ALSI is a commonly adopted benchmark for South African equity funds due to its down-weighting of share ownership limits – specifically the foreign ownership of domestic stocks assumed to be tightly held and non-tradable. As such it represents a reasonable benchmark index for the momentum portfolios found in this report. Additionally, to approximately match the period over which the momentum strategies are conducted, the yield on the 10-year R186 government bond has been selected as the hurdle rate.

Whilst the inclusion of stocks based on their end-of-sample market capitalisation introduces elements of survivorship and look-ahead biases into this data, the impracticality of reselecting stocks based on their daily market capitalisations outweighs the gains of doing so. Given that this report establishes portfolios based only on those stocks available to the investor in any given time period, these biases are unlikely to have a material impact on the implementation or relative performance of the strategies described below. For similar reasons of impracticality, all transaction costs are ignored for this report so as not to distract from the core effectiveness of the momentum strategies.

3.2. Research methods

This chapter is divided into several further sub-chapters to discuss each of the research methods outlined in chapter 2. Both the time-series and cross-sectional momentum portfolio approaches are presented in sub-chapter 3.2.1. Following this, sub-chapter 3.2.2. presents the methods employed to identify momentum crash periods.

3.2.1. Momentum portfolio strategies

This report examines the performance of several cross-sectional strategies and time-series strategies. Both the decile cross-sectional strategies (Moskowitz et al (2012)), and top half minus bottom half cross-sectional strategies (Goyal and Jegadeesh (2015)) will be examined. For all portfolios, stocks are grouped based on their prior returns over the formation period. Daniel and Moskowitz (2013) tested only a 12x1 cross-sectional decile WML portfolio approach for momentum crashes, thus emphasising that only holding periods of 1-month are of significant importance for crash investigation. As such, this report continues on this track by testing varying formation periods against a 1-month holding period.

The following strategy array is generated for the cross-sectional and time-series portfolios:

(1x1) (2x1) (3x1) (4x1) (5x1) (6x1) (12x1) (18x1) (24x1) (36x1) (48x1) (60x1).

This array of strategies allows for both short-term (<= 12 months) and long-term (> 12 months) momentum generation as identified in chapter 2. The array is reconstructed for both the decile and halves cross-sectional approaches, the two time-series approaches, and the two zero return threshold time-series approaches. Additionally, given the importance placed on the 12x1 WML strategy by Daniel and Moskowitz (2013), this report will use the same strategy (both cross-sectional and time-series) as a base-case from which to draw comparison.

For the decile cross-sectional strategies, at each formation date, all stocks' formation period excess returns are calculated and compared to the 10^{th} and 90^{th} percentile of all the sample stocks' formation period returns. Stocks that exhibit formation returns greater than the 90^{th} percentile are equally-weighted and added to the winner portfolio. Similarly, stocks that exhibit formation returns less than the 10^{th} percentile are equally-weighted and added to the loser portfolio. This strategy then goes R1 long in the winner and R1 short in the loser portfolios to create the WML portfolio. Thus the WML portfolio is always forced to be net investment-neutral.

Returns to the cross-sectional decile strategy CS deciles are calculated as follows:

$$CS\ deciles{:}\ Eq.1.\ \ R_t^{CS} = \frac{1}{N^L}\sum\nolimits_{R_{i,t-1} \geq R_{t-1}^{90th}} R_{it} - \frac{1}{N^S}\sum\nolimits_{R_{i,t-1} < R_{t-1}^{10th}} R_{it},$$

where $R_{i,t-1}$ is the formation period excess return on the ith stock, R_{t-1}^{90th} is the 90th percentile of formation period excess returns, R_{t-1}^{10th} is the 10th percentile of formation period excess returns, and N^L (N^S) is the number of stocks in the winner (loser) portfolio. Similar to Moskowitz et al (2012), this strategy invests R1 over each month in each of the two portfolios; thus always being net investment-neutral. Similar construction is completed for the top half minus bottom half cross-sectional approach (CS halves), where the 90th percentile and 10th percentile of formation period returns are replaced with the cross-sectional average of formation period returns:

$$CS\ halves{:}\ Eq.2.\ \ R_t^{CS} = \frac{1}{N^L}\sum\nolimits_{R_{i,t-1} \geq \overline{R_{t-1}}} R_{it} - \frac{1}{N^S}\sum\nolimits_{R_{i,t-1} < \overline{R_{t-1}}} R_{it}.$$

Goyal and Jegadeesh (2015) investigated the top half minus bottom half approach "so that the results are more directly comparable with the [time-series] strategy" (Goyal and Jegadeesh, 2015) and as such these strategies are provided for in this report.

For the time-series strategies, at each formation date all stocks' formation period excess returns are calculated and compared to a zero threshold i.e. the stocks' raw formation return is compared to the risk-free return. Stocks that exhibit formation returns in excess of the risk-free return (excess returns greater or equal to zero) are equally-weighted and added to the winner portfolio. Stocks that exhibit formation excess returns less than zero are equally-weighted and added to the loser portfolio. As with the cross-sectional approaches, this strategy then goes R1 long in the winner and R1 short in the loser portfolios to create the WML portfolio. This strategy also forces a zero net investment in every month of trading, similar to the cross-sectional approaches.

Returns to the time-series strategy with zero net exposure (TS NE=0) are thus calculated as follows:

$$TS\ NE = 0: Eq. 3.\ \ R_t^{TS} = \frac{1}{N^L}\sum\nolimits_{R_{i,t-1}\geq 0} R_{it} - \frac{1}{N^S}\sum\nolimits_{R_{i,t-1}<0} R_{it},$$

where $R_{i,t-1}$ is the formation period excess return on the i[th] stock, and N^L (N^S) is the number of stocks in the winner (loser) portfolio. Goyal and Jegadeesh (2015) define the scaled returns to variable net exposure time-series approach (TS NE=variable) as follows:

$$TS\ NE = variable: Eq. 4.\ \ R_t^{TS}(scaled) = \frac{2}{N}(\sum\nolimits_{R_{i,t-1}\geq 0} R_{it} - \sum\nolimits_{R_{i,t-1}<0} R_{it}).$$

As described by Goyal and Jegadeesh (2015), this strategy has inherent market timing and risk premium components of return due to the fixed threshold for asset selection (see sub-chapter 2.2). This definition of time-series returns makes no assumptions about the aggregate investment, understanding that in many months of trading the strategy will result in unequal number of stocks on the long and short sides. Eq. 4's specification of returns is likely to outperform that of Eq. 3's approach, given that Eq. 3 forces the strategy to be investment-neutral and thereby loses out on the market timing and risk premium elements.

Following Goyal and Jegadeesh's (2015) specification, the monthly risk premium and market timing returns to time-series strategies are calculated as follows:

$$Eq. 5.\ \ RP_t = \overline{NetLong}\ x\ \overline{R_t}$$

$$Eq. 6.\ \ MT_t = (NetLong_t - \overline{NetLong})x\ \overline{R_t},$$

where $\overline{NetLong}$ is the average net long position in stocks over the sample, $\overline{R_t}$ is the return to the equally-weighted index at time t, and $NetLong_t$ is the net long position at time t.

Finally, this report presents an alternative time-series approach with the intent of examining the impact of a different threshold for asset selection on the returns to time-series portfolios. This investigation is ideologically similar to the comparison of the returns to varying cross-sectional quantile cut-offs. Where Moskowitz et al (2012) and Goyal and Jegadeesh (2015) specify that the time-series approach selects stocks based on their formation period's excess returns (i.e. zero excess return threshold), this specification uses a zero absolute return threshold.

These portfolios are constructed in a manner akin to the TS NE=0 (Eq. 3) portfolios, replacing only the stock's formation period excess return with the corresponding 'raw' return. The returns to the zero absolute threshold time-series approach with zero net exposure (TSAlt NE=0) are calculated as follows:

$$TSAlt\ NE = 0 : Eq. 7.\ \ R_t^{TSAlt} = \frac{1}{N^L} \sum\nolimits_{r_{i,t-1} \geq 0} R_{it} - \frac{1}{N^S} \sum\nolimits_{r_{i,t-1} < 0} R_{it},$$

where $r_{i,t-1}$ is the formation period 'raw' return on the i[th] stock, and N^L (N^S) is the number of stocks in the winner (loser) portfolio. For completeness, the scaled returns to the zero absolute threshold time-series approach with variable net exposure (TSAlt NE=variable), as modelled on Goyal and Jegadeesh's (2015) time-series approach, are calculated as follows:

$$TSAlt\ NE = variable : Eq. 8.\ \ R_t^{TSAlt}(scaled) = \frac{2}{N} \left(\sum\nolimits_{r_{i,t-1} \geq 0} R_{it} - \sum\nolimits_{r_{i,t-1} < 0} R_{it}\right).$$

3.2.2. Momentum crashes

The second research method follows the line of Daniel and Moskowitz (2013) by identifying months of the momentum trading strategy which resulted in substantially negative excess returns. Where Daniel and Moskowitz (2013) focused on the 15 worst monthly momentum returns, this report will identify any month where momentum generates excess losses greater than 10%. These months represent losses which exceed the 10% stop-loss strategy found to be commonly employed by market constituents (Han et al (2014)) and as such are deemed highly relevant in practical application.

Daniel and Moskowitz (2013) defined momentum crash scenarios as significant momentum losses sustained over multiple months. This report will continue on this thought by identifying similar scenarios in the cumulative returns of both cross-sectional and time-series momentum. Finally, they found that their 12x1 CS deciles strategy exhibited substantial negative skewness, and they attributed this to the uncommon events where significant momentum losses were made over extended periods of time – momentum crash scenarios. This report will thus investigate the skewness of each of the momentum strategies employed to identify any trends in momentum crashes.

4. Results

Chapter 4 presents multiple sub-chapters of results to emphasise the aims of the report. Included in this chapter are sub-chapters 4.1. and 4.2. which, respectively, present the results of the analysis of cross-sectional momentum and time-series momentum in South African common stocks over the period 2002.02-2015.05. Sub-chapter 4.3. presents an alternative approach to time-series momentum trading by altering the fixed threshold for asset selection. Sub-chapter 4.4. then presents the momentum crash investigation over this full time period.

4.1. Cross-sectional momentum strategy results

Table 4.1. presents the first three annualised return moments of the 12 tested monthly decile cross-sectional momentum portfolios for the period 2002.02-2015.15. All transaction costs are ignored. These portfolios are constructed in accordance with Moskowitz et al's (2012) portfolios.

Table 4.1.: Cross-sectional momentum portfolio characteristics (deciles), 2002.02-2015.05

This table presents the characteristics of the monthly decile cross-sectional momentum portfolios' (CS deciles) excess returns over the period 2002.02-2015.05. The mean excess returns and standard deviations are in percent and annualised, whilst the Sharpe ratio is also annualised. Returns to the "winner minus loser" (WML) portfolio are calculated as according to Eq. 1. The cross-sectional momentum strategies are written in the form: (formation period) x (holding period).

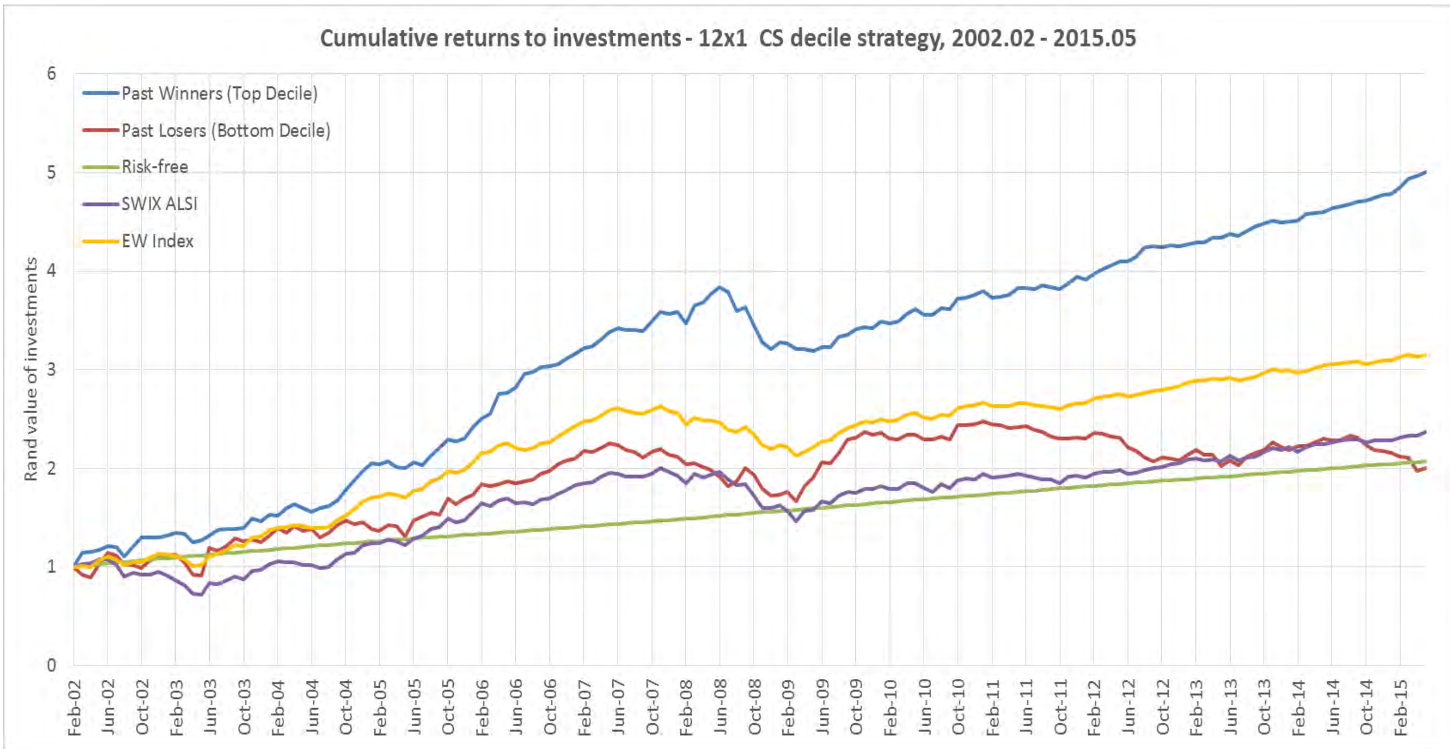
CS deciles	1x1	2x1	3x1	4x1	5x1	6x1	12x1	18x1	24x1	36x1	48x1	60x1
Excess return to winner, R_W	12.24	16.22	21.00	24.60	27.33	29.16	30.21	26.41	26.48	24.42	22.27	17.40
Excess return to loser, R_L	21.35	19.93	13.70	12.89	13.21	8.36	7.59	8.01	10.00	7.70	8.47	13.86
Return to WML, R_{WML}	-9.11	-3.71	7.31	11.71	14.12	20.80	22.63	18.40	16.48	16.72	13.79	3.54
T-statistic: $t(R_{WML})$	-1.60	-0.61	1.22	1.94	2.23	3.17	3.39	2.88	2.64	2.64	2.36	0.64
Standard deviation, σ_{WML}	20.72	22.09	21.87	22.02	23.09	23.99	24.35	23.37	22.77	23.16	21.38	20.22
Skew, SK_{WML}	0.53	0.30	0.07	-0.31	-0.21	-0.14	-0.41	-0.17	-0.13	-0.04	0.25	0.14
Sharpe ratio, SR_{WML}	-0.44	-0.17	0.33	0.53	0.61	0.87	0.93	0.79	0.72	0.72	0.65	0.18

Of the 12 CS deciles strategies, only the 1x1, 2x1, 3x1 and 60x1 WML portfolios fail to achieve positive significantly positive returns, even though these returns are economically significant. Both the 1x1 and 2x1 WML portfolios earn statistically insignificant but economically significant negative returns (-9.11% p.a. and -3.71% p.a.), thereby confirming Jegadeesh and Titman's (1993) short-term lagged reaction consideration and short-term contrarian profits. In contrast, the 60x1 WML on average earns 3.54% per annum which, although statistically insignificant, also remains economically significant over the long formation period.

Particular attention is drawn to the 12x1 base-case strategy, the highest return-generating strategy. The WML portfolio generates statistically and economically significant investment-neutral returns of 22.63% per annum on average (t-statistic = 3.39), with a Sharpe ratio of 0.93. In contrast, the SWIX ALSI benchmark averaged 10.30% excess return per annum over the period with a Sharpe ratio of 0.68. Given that any investment in the benchmark is long-only by default, it is more appropriate to compare the benchmark return with the long-only winner portfolio so as to create direct comparability between the investment positions. Over the full sample, the 12x1 winner decile averages 30.21% excess return (Sharpe ratio of 1.56) and outperforms the SWIX ALSI benchmark both economically (19.91% p.a.) and statistically (t-statistic = 5.23). Figure 4.1. demonstrates this comparison aptly, by presenting a graphical comparison of the cumulative returns to long investments in the 12x1 portfolios and the benchmark and risk-free asset.

Figure 4.1.: Cumulative returns to investments – 12x1 decile strategy, 2002.02-2015.05

This figure plots the cumulative returns over the period 2002.02-2015.05 for four key investments: the 12x1 top decile "past winner" portfolio, the 12x1 bottom decile "past loser" portfolio, the risk-free asset, and the benchmark – the Shareholder-weighted All-Share Index (SWIX ALSI). This plot assumes a R1 investment in each of the four assets over each month, beginning in February 2002. With the exception of the risk-free asset, all investments' returns are presented in excess of the risk-free rate of return.



Consistent with the literature, this sample shows a substantial return premium to a long-only investment in the 12x1 decile winner portfolio over a long-only investment in the market-type benchmark. Where Daniel and Moskowitz's (2013) 12x1 decile loser portfolio earned average losses of 6.1% per annum, this loser portfolio experienced an average excess gain of 7.59% per annum. As such a contrarian investment in the loser portfolio yields 15.67% per annum on average, over the full sample. This short loser portfolio therefore merely represents a funding portfolio for the long winner, where Daniel and Moskowitz's (2013) short loser also generated favourable returns to the trader. On further investigation, the second and third best performing strategies (6x1 and 18x1 decile strategies) exhibit similar characteristics to the 12x1 decile strategy with strong outperformance on the long side and return-reducing, funding portfolio on the short side (Appendix B1).

Table 4.2. below presents the first three annualised return moments of the 12 tested monthly top half minus bottom half cross-sectional momentum portfolios for the period 2002.02-2015.05. These portfolios are constructed in a fashion similar to that introduced by Goyal and Jegadeesh (2015) for comparability with the time-series portfolios in sub-chapter 4.2. Again, all transaction costs are ignored.

Table 4.2.: Cross-sectional momentum portfolio characteristics (halves), 2002.02-2015.05

This table presents the characteristics of the monthly top half minus bottom half cross-sectional momentum portfolios' excess returns over the period 2002.02-2015.05. The mean excess returns and standard deviations are in percent and annualised, whilst the Sharpe ratio is also annualised. Returns to the "winner minus loser" (WML) portfolio are calculated as according to Eq. 1. The cross-sectional momentum strategies are written in the form: (formation period) x (holding period).

	1x1	2x1	3x1	4x1	5x1	6x1	12x1	18x1	24x1	36x1	48x1	60x1
Excess return to winner, R_W	14.19	15.71	15.65	17.80	17.62	18.68	19.89	20.26	19.70	17.82	18.26	17.79
Excess return to loser, R_L	18.15	16.79	16.71	14.59	14.69	13.52	12.20	11.99	12.33	13.83	13.34	13.75
Return to WML, R_{WML}	-3.96	-1.08	-1.06	3.21	2.93	5.16	7.69	8.26	7.37	3.99	4.93	4.03
T-statistic: $t(R_{WML})$	-1.82	-0.41	-0.39	1.25	1.15	1.99	2.84	3.02	2.66	1.44	1.92	1.65
Standard deviation, σ_{WML}	7.95	9.52	9.87	9.35	9.34	9.47	9.89	9.99	10.13	10.12	9.39	8.92
Skew, SK_{WML}	0.09	-0.21	-0.57	-0.52	-0.78	-0.71	-0.72	-0.61	-0.71	-0.52	-0.48	0.01
Sharpe ratio, SR_{WML}	-0.50	-0.11	-0.11	0.34	0.31	0.54	0.78	0.83	0.73	0.39	0.52	0.45

Table 4.2. again confirms the existence of Jegadeesh and Titman's (1993) short-term contrarian profitability through investment in the 1x1, 2x1 and 3x1 WML portfolios (-3.96% p.a., -1.08% p.a. and -1.06% p.a.). In contrast to the decile portfolios however, only four of the top half minus bottom half WML strategies yield statistically significant returns. As expected, all of the top half minus bottom half strategies earn substantially smaller returns than their corresponding decile strategies due to less extreme spread between the winner and loser portfolios' respective stock returns (Goyal and

Jegadeesh, 2015). The reduction in spread is evident in the lower standard deviation when comparing each top half minus bottom half WML portfolio with its decile WML counterpart.

Given the above-mentioned two moments, four of the top half minus bottom half WML portfolios actually experience a higher Sharpe ratio than their corresponding decile WML portfolio (2x1, 18x1, 24x1 and 60x1); however only the 18x1 and 24x1 WML strategies yield statistically significant returns in any case. Moreover, none of these ratios exceed the 0.93 Sharpe achieved by the 12x1 decile WML portfolio. The 12x1 base-case again generates significantly positive investment-neutral profits of 7.69% per annum (t-statistic = 2.84), with similar characteristic of outperformance on the long side (9.59%, t-statistic = 4.44) and funding portfolio on the short side. The top half minus bottom half portfolios will be examined further in sub-chapter 4.2.

4.2. Time-series momentum strategy results

Table 4.3. presents the annualised return moments of the 12 tested monthly time-series momentum portfolios for the period 2002.02-2015.15. Panel A of Table 4.3. presents the moments as defined according to the time-series approach with zero net investment exposure (TS NE=0 - Eq.3.) approach and Panel B presents the same moments as defined by the variable investment exposure time-series approach (TS NE=variable - Eq. 4.). Notice that TS NE=0 separates the strategy into a long winner and short loser as opposed to the winner minus loser portfolio only by TS NE=variable. All transaction costs are ignored in Table 4.3.

Table 4.3.: Time-series momentum portfolio characteristics, 2002.02-2015.05

This table presents the characteristics of the monthly time-series momentum portfolios' excess returns over the period 2002.02-2015.05. Panel A presents the first three moments of the investment-neutral approach (TS NE=0, Eq. 3), while Panel B presents the same moments from the non-zero net exposure approach (TS NE=variable, Eq. 4). The mean excess returns and standard deviations are in percent and annualised, whilst the Sharpe ratio is also annualised. The time-series momentum strategies are written in the form: (formation period) x (holding period).

Panel A, TS NE=0	**1x1**	**2x1**	**3x1**	**4x1**	**5x1**	**6x1**	**12x1**	**18x1**	**24x1**	**36x1**	**48x1**	**60x1**
Excess return to winner, R_W	15.47	17.05	17.24	18.83	18.20	19.08	17.08	14.91	17.89	17.05	17.95	17.79
Excess return to loser, R_L	17.97	15.97	12.62	10.99	11.55	7.49	8.26	9.21	10.37	10.71	11.36	12.12
Return to WML, R_{WML}	-2.50	1.08	4.61	7.83	6.65	11.59	8.82	5.70	7.52	6.34	6.59	5.67
T-statistic: $t(R_{WML})$	-0.87	0.35	1.61	2.45	1.94	3.08	2.16	1.43	1.83	1.55	1.59	1.50
Standard deviation, σ_{WML}	10.45	11.34	10.50	11.70	12.50	13.73	14.94	14.50	15.02	14.97	15.15	13.78
Skew, SK_{WML}	-0.12	0.04	-0.32	-0.34	-0.74	-0.88	-0.57	-0.62	-0.20	0.01	0.29	0.23
Sharpe ratio, SR_{WML}	-0.24	0.10	0.44	0.67	0.53	0.84	0.59	0.39	0.50	0.42	0.44	0.41

Panel B, TS NE=variable	**1x1**	**2x1**	**3x1**	**4x1**	**5x1**	**6x1**	**12x1**	**18x1**	**24x1**	**36x1**	**48x1**	**60x1**
Return to TS, R_{TS}	9.29	15.29	16.90	18.39	18.62	23.29	25.92	20.00	19.00	19.00	19.49	21.66
T-statistic: $t(R_{TS})$	2.51	3.72	3.82	3.97	3.87	4.88	5.23	3.73	3.69	3.75	3.73	3.86
Standard deviation, σ_{TS}	13.50	15.03	16.17	16.93	17.57	17.43	18.08	19.59	18.80	18.52	19.09	20.48
Skew, SK_{TS}	0.69	0.24	-0.21	0.19	0.31	0.53	0.26	-0.16	-0.27	-0.46	-0.97	-0.83
Sharpe ratio, SR_{TS}	0.69	1.02	1.05	1.09	1.06	1.34	1.43	1.02	1.01	1.03	1.02	1.06

Complementary to the literature, all time-series portfolios earn positive excess returns when not forced into an investment-neutral exposure (Panel B). The same cannot be said of the TS NE=0 strategies (Panel A). Whilst Panel A results in all but the 1x1 time-series strategy generating positive returns, only four of the WML strategies yield statistically significantly positive results (4x1, 6x1, 12x1, 24x1). Of these results, the TS NE=0 6x1 WML strategy yields the largest returns to the trader with average profits of 11.59% per annum. Interestingly, a long-only investment in any of TS NE=0 strategies would yield significant returns above the SWIX ALSI benchmark, with the 6x1 WML again achieving the largest outperformance of 8.78% per annum (t-statistic = 3.61).

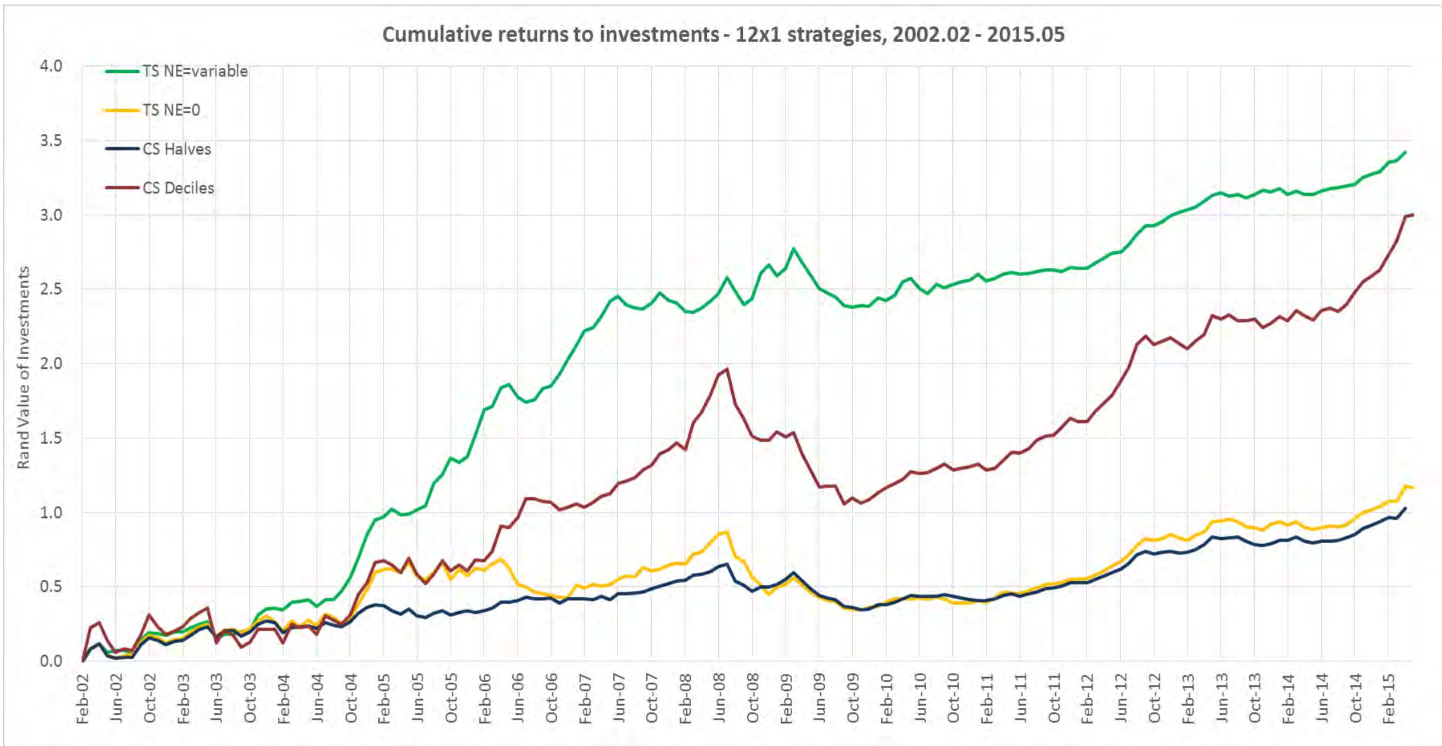
The 12x1 WML base-case strategy yields the second highest zero investment profit of 8.82% per annum on average, although at a far lower Sharpe ratio (Sharpe ratio = 0.59) than the cross-sectional equivalent. The long winner portfolio generates a Sharpe ratio of 1.15 (returns of 17.08% p.a.) while the short loser portfolio confirms the funding portfolio previously discussed with a Sharpe equal to 0.47 and average excess returns of 8.26% per annum.

Table 4.3. further shows that all TS NE=variable returns (Panel B) strongly exceed that of the corresponding TS NE=0 strategy (Panel A). These higher return strategies (Panel B) also all exhibit risk (standard deviation of returns) larger than the corresponding lower return strategies (Panel A), although disproportionate to the increase in returns. As such, every single time-series strategy in Panel B of Table 4.3. achieves a significantly larger Sharpe ratio than the corresponding Panel A strategy. Additionally, every Panel B strategy except the 1x1 portfolio achieves a Sharpe ratio in excess of the 12x1 decile cross-sectional strategy (Sharpe ratio = 0.93), the previous best return-to-risk earner.

In the case of Panel B of Table 4.3., the 12x1 base-case time-series strategy earns the highest investment-neutral returns averaging 25.92% per annum (Sharpe ratio = 1.43). This strategy, as confirmed by the literature, outperforms the 12x1 decile WML cross-sectional strategy both on an absolute returns basis and on a risk-adjusted basis (cross-sectional approach: 22.63%, Sharpe ratio = 0.93). Figure 4.2. below presents the cumulative returns to both the 12x1 base-case time-series strategies as well as the above-mentioned 12x1 base-case cross-sectional strategies.

Figure 4.2.: Cumulative returns to investments – 12x1 strategies, 2002.02-2015.05

This figure plots the cumulative returns to the four 12x1 momentum strategies over the period 2002.02-2015.05: the investment-neutral time-series strategy (TS NE=0, Eq. 3), the variable exposure time-series strategy (TS NE=variable, Eq. 4), the cross-sectional top decile minus bottom decile strategy (CS deciles), and the cross-sectional top half minus bottom half strategy (CS halves).



The 12x1 TS NE=0 approach of Panel A of Table 4.3. appears to mimic the returns of the 12x1 CS halves strategy with similar movements being experienced over most of the sample. Over the sub-period October 2004 to June 2006 however the strategies deviate somewhat where the TS NE=0 approach follows the CS deciles approach, before returning to the original mimic of the CS halves approach. This draws a practical question about the implementation of a combined CS halves and TS NE=0 approach, especially on an industry-applied long-only mandate. The combined approach is similar in nature to the CS halves strategy, however only stocks with positive returns are added to the long winner (time-series element). Figure 4.3. presents the long-only winner portfolios of the CS halves approach, TS NE=0 approach, and the combined CS halves and TS NE=0 strategy (CS halves long>0).

Figure 4.3.: Cumulative returns to investments – 12x1 long-only strategies, 2002.02-2015.05

This figure plots the cumulative returns to three 12x1 long-only momentum strategies over the period 2002.02-2015.05: the cross-sectional top half minus bottom half strategy (CS halves long, the investment-neutral time-series strategy (TS NE=0 long, Eq. 3), and the cross-sectional top half minus bottom half strategy with a zero return threshold (CS halves long>0).

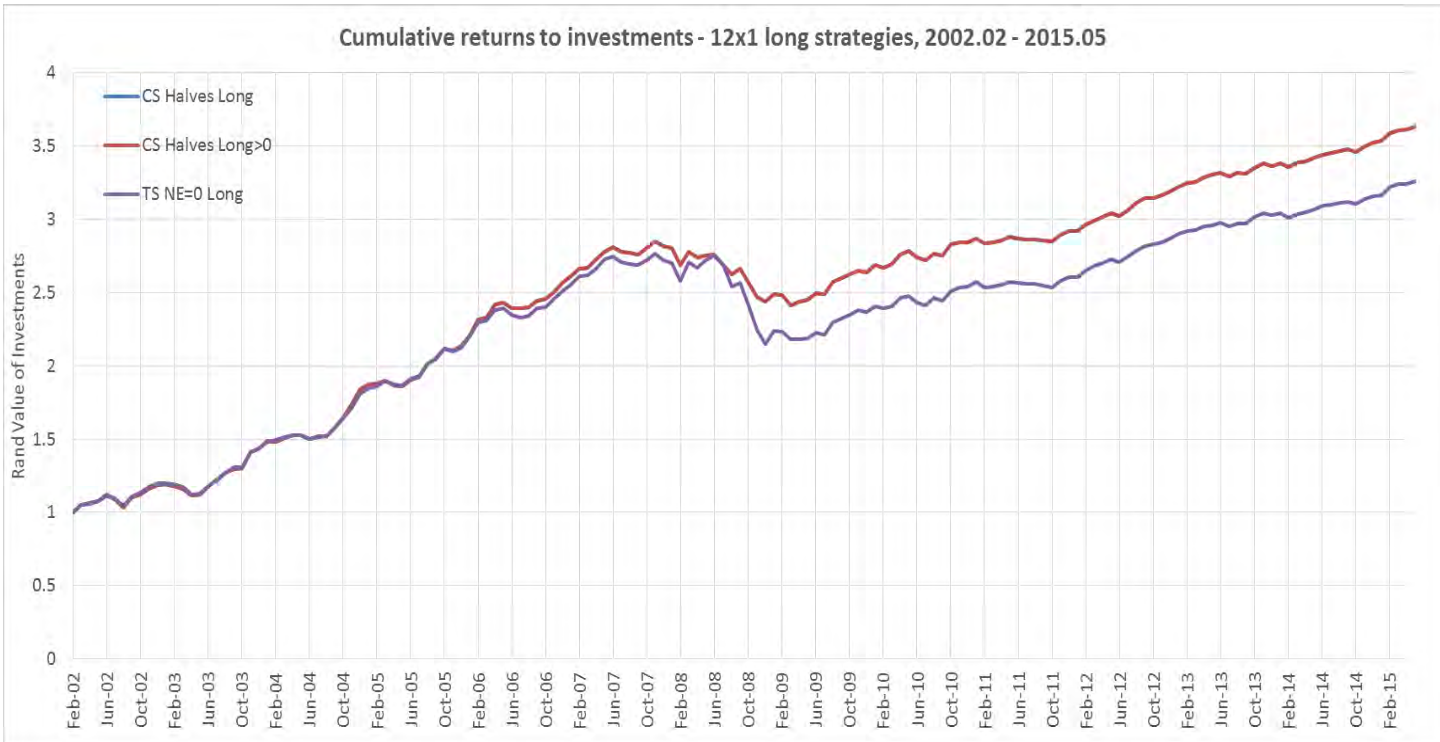


Figure 4.3. confirms that the 12x1 CS halves long-only mandate achieves better annualised returns on average (19.89% p.a.) than the 12x1 TS NE=0 strategy (17.08% p.a.). However, the combined TS NE=0 and CS halves approach yields long-only returns equal to the long-only 12x1 CS halves strategy. This is an interesting, yet unsurprising finding given that the combined strategy accepts stocks into the winner portfolio only when the stock achieves returns above the cross-sectional average AND above zero. Considering that the cross-sectional average return is positive in a supermajority of months over the sample, the zero absolute returns threshold does not remove any stocks from consideration for the long winner portfolio. As such, returns to the two long-only portfolios are equivalent in bull markets. Further studies may examine this approach over periods and in markets where the trend of the market is different to this, so as to determine whether the extra asset selection criteria improves returns to the CS halves strategy.

Reconsidering Figure 4.2., two elements are of particular interest to this study. Firstly, the substantial deviation between the TS NE=variable and CS halves strategies implies that there are drivers of returns to the time-series approach that are not apparent in the cross-sectional approach. This finding is consistent with Goyal and Jegadeesh's (2015) work, and is discussed further below. The second element is the substantial downturn in the cumulative returns to the CS deciles approach over the sub-period June 2008 to October 2009. This finding will be discussed further in sub-chapter 4.4.

As outlined previously, Goyal and Jegadeesh (2015) attributed the difference in returns between the TS NE=variable approach and corresponding CS halves strategy to three return elements: market timing, risk premium, and stock selection. Using Eq. 5 for the risk premium return and Eq. 6 for the market timing return, Table 4.4. presents a decomposition of the sources of returns to the time-series approach.

Table 4.4.: Sources of time-series momentum returns (TS NE=variable), 2002.02-2015.05

This table presents a decomposition of the four sources of the monthly time-series momentum portfolios' (TS NE=variable) returns over the period 2002.02-2015.05. All returns – including the equally-weighted index excess return (EW Index) are in percent and annualised, with the corresponding t-statistic in brackets. Returns to the cross-sectional halves (CS halves) approach are calculated by Eq. 2, returns to non-zero net exposure the time-series (TS NE=variable) approach are calculated by Eq. 4, risk premium (RP) returns are calculated by Eq. 5, market timing (MT) returns are calculated by Eq. 6, with stock selection (SS) comprising the remainder of the return difference. The average net long position (Net Long) attributed to the time-series approach over the period is also in percent.

	CS halves	**TS NE=variable**	**Difference**	**RP**	**MT**	**SS**	**Net Long**
1x1	-3.96 (-1.82)	9.29 (2.51)	13.25 (4.34)	1.87 (4.52)	3.79 (2.52)	7.59 (4.30)	11.48 (3.77)
2x1	-1.08 (-0.41)	15.29 (3.72)	16.37 (4.41)	3.00 (4.52)	3.74 (2.11)	9.62 (4.57)	18.49 (5.62)
3x1	-1.06 (-0.39)	16.90 (3.82)	17.96 (4.64)	3.59 (4.52)	3.11 (1.72)	11.27 (5.12)	22.06 (6.51)
4x1	3.21 (1.25)	18.39 (3.97)	15.19 (4.04)	4.12 (4.52)	2.50 (1.34)	8.56 (4.25)	25.37 (7.48)
5x1	2.93 (1.15)	18.62 (3.87)	15.69 (4.13)	4.47 (4.52)	2.98 (1.53)	8.24 (4.17)	27.50 (8.21)
6x1	5.16 (1.99)	23.29 (4.88)	18.14 (4.74)	4.67 (4.52)	3.46 (1.79)	10.01 (4.85)	28.71 (8.52)

12x1	7.69 (2.84)	25.92 (5.23)	18.24 (4.28)	6.04 (4.52)	3.74 (1.70)	8.46 (3.77)	37.15 (10.31)
18x1	8.26 (3.02)	20.00 (3.73)	11.74 (2.55)	6.27 (4.52)	2.70 (1.18)	2.78 (0.94)	38.56 (10.66)
24x1	7.37 (2.66)	19.00 (3.69)	11.63 (2.63)	6.35 (4.52)	0.45 (0.23)	4.83 (1.77)	39.03 (11.07)
36x1	3.99 (1.44)	19.00 (3.75)	15.01 (3.30)	7.03 (4.52)	0.23 (0.15)	7.76 (2.85)	43.24 (14.92)
48x1	4.93 (1.92)	19.49 (3.73)	14.57 (2.98)	7.82 (4.52)	-0.38 (-0.30)	7.12 (2.51)	48.13 (18.15)
60x1	4.03 (1.65)	21.66 (3.86)	17.62 (3.24)	8.61 (4.52)	-0.48 (-0.36)	9.49 (2.42)	52.99 (20.69)

Table 4.4. shows similar trends to that identified by Goyal and Jegadeesh (2015). The net long position of the time-series approach increases monotonically with formation period length from 11.48% for the 1x1 strategy to 52.99% for the 60x1 strategy. Given that the equally-weighted index averages positive returns over the sample, the risk premium attributed to time-series momentum also increases monotonically with formation period, from 1.87% p.a. for the 1x1 strategy to 8.61% p.a. for the 60x1 strategy.

The market timing component is found to be significant only for short-term formation periods (1-month: t-statistic = 2.52, 2-months: t-statistic = 2.11), while long-term formation period strategies ultimately earn insignificantly negative market timing returns (48-months: t-statistic = -0.30; 60-months: t-statistic = -0.36). Finally, the stock selection component is significant for all formation periods except the 18x1 strategy. This element, like the difference in returns itself, exhibits no identifiable trend. Thus the stock selection component is likely a function of some further unobservable induced component; something to be considered in future research.

Moreover, Table 4.4.'s decomposition of TS NE=variable returns further reveals that for the 12x1 base-case strategies, both the risk premium and the stock selection components contribute both economically and statistically significant returns (t-statistics = 4.51 and 3.77 respectively). Considering the significant excess return of 16.26% per annum to the equally-weighted index and 10.30% per annum to the SWIX ALSI, it is clear to see that any TS NE=variable strategy with an average net long position would earn significant compensation attributable to the market – as such the risk premium is intuitive. This is immensely evident in both the literature and the strong risk premium in this report (6.05% p.a.).

It is not overwhelmingly clear however, how the TS NE=variable strategy better selects future winner and loser stocks than the CS halves strategy. This is likely a function of the opposing thresholds for asset selection, of which the TS NE=variable approach holds extra information; future studies may resolve this question. That the stock selection component contributes such a significant portion of returns to the 12x1 time-series (8.46% p.a.) bears stark contrast to the literature where the component adds no significant return for medium- to long-term formation period strategies. Finally, the market timing component does not contribute significantly on a statistical basis, even though the return is economically significant (3.74% p.a.). Appendix C presents a graphical illustration of the cumulative returns to these three return components, for the 12x1 base-case time-series strategy.

A final set of regression analyses was conducted for the time-series and cross-sectional strategies. When regressing excess time-series momentum returns as the independent variable on the dependent decile cross-sectional momentum excess returns, significant intercept terms are apparent for the short-term formation period strategies but not for any others (1x1: t-statistic = -3.16, 2x1: t-statistic = -2.39). Similarly, with time-series momentum as the independent and cross-sectional top half minus bottom half momentum returns as the dependent variable, only the 1x1, 2x1 and 3x1 strategies exhibit significant intercepts (t-statistics = -3.80, -2.28, -2.49 respectively). As such, time-series momentum appears to fully capture cross-sectional momentum for medium- to long-term formation period strategies but not for short-term.

Conversely, when the decile cross-sectional momentum returns are regressed as the independent variable and the time-series momentum returns as the dependent, no significant intercept terms are found for any of the tested strategies. This finding is reaffirmed when conducting the same regressions, replacing the decile cross-sectional strategy with the corresponding top half minus bottom half cross-sectional approach (see Appendix D). Thus, the time-series approach to momentum wholly subsumes the cross-sectional approach. This is made abundantly clear when considering the large differences in returns attributable to Goyal and Jegadeesh's (2015) risk premium, market timing and stock selection as seen above.

4.3. An alternative time-series approach: Zero absolute returns threshold (TSAlt)

Table 4.5. presents the first three annualised return moments of the 12 tested monthly time-series momentum portfolios employed with the zero absolute returns threshold for asset selection (TSAlt), for the period 2002.02-2015.15. Panel A of Table 4.5. presents the moments of the investment-neutral zero absolute threshold time-series approach (TSAlt NE=0, Eq. 7), and Panel B presents the same moments of the variable exposure zero absolute threshold time-series strategies (TSAlt NE=variable, Eq. 8). Notice that TSAlt NE=0 separates the strategy into a long winner and short loser as opposed to the winner minus loser only by TSAlt NE=variable. Panel C presents the induced return components of the decomposition of the TSAlt NE=variable strategies' returns, as in sub-chapter 4.2. Again, all transaction costs are ignored.

Table 4.5.: Time-series momentum portfolio characteristics, 2002.02-2015.05

This table presents the characteristics of the zero absolute threshold monthly time-series momentum portfolios' excess returns over the period 2002.02-2015.05. Panel A presents the first three moments of the investment-neutral strategies (TSAlt NE=0) strategies while Panel B presents same moments of the non-zero investment approach (TSAlt NE=variable). The mean excess returns and standard deviations are in percent and annualised, whilst the Sharpe ratio is also annualised. Panel C presents the decomposition of the returns to the TSAlt NE=variable approach, as in Table 4.4. The time-series momentum strategies are written in the form: (formation period) x (holding period). Figures in brackets are implied t-statistics.

Panel A, TSAlt NE=0	**1x1**	**2x1**	**3x1**	**4x1**	**5x1**	**6x1**	**12x1**	**18x1**	**24x1**	**36x1**	**48x1**	**60x1**
Excess return to winner, R_W	15.99	16.97	16.97	18.26	17.80	17.40	16.33	15.30	17.21	16.77	17.05	16.44
Excess return to loser, R_L	17.54	16.06	12.02	9.41	10.26	7.29	8.89	8.90	9.62	7.76	8.97	12.43
Return to WML, R_{WML}	-1.55	0.91	4.95	8.85	7.53	10.11	7.44	6.40	7.59	9.01	8.08	4.02
T-statistic: $t(R_{WML})$	3.57	4.38	4.51	4.74	4.63	5.46	5.51	4.07	4.59	5.15	4.73	4.14
Standard deviation, σ_{WML}	10.49	12.08	11.62	11.55	13.16	14.52	17.02	16.82	16.70	19.30	22.39	20.40
Skew, SK_{WML}	-0.13	-0.27	-0.32	-0.32	-0.56	-0.54	-0.89	-0.47	-0.39	-0.22	1.04	1.37
Sharpe ratio, SR_{WML}	-0.15	0.08	0.43	0.77	0.57	0.70	0.44	0.38	0.45	0.47	0.36	0.20

Panel B, TSAlt NE=variable	**1x1**	**2x1**	**3x1**	**4x1**	**5x1**	**6x1**	**12x1**	**18x1**	**24x1**	**36x1**	**48x1**	**60x1**
Return to TS, R_{TS}	13.37	18.21	20.44	22.00	22.20	25.47	28.09	22.44	24.28	27.09	28.19	25.02
T-statistic: $t(R_{TS})$	3.57	4.38	4.51	4.74	4.63	5.46	5.51	4.07	4.59	5.15	4.73	4.14
Standard deviation, σ_{TS}	13.66	15.18	16.56	16.95	17.49	17.05	18.60	20.15	19.31	19.19	21.74	22.06
Skew, SK_{TS}	0.67	0.29	-0.03	0.25	0.34	0.49	0.05	-0.24	-0.33	-0.78	-0.82	-0.62
Sharpe ratio, SR_{TS}	0.98	1.20	1.23	1.30	1.27	1.49	1.51	1.11	1.26	1.41	1.30	1.13

Panel C	**1x1**	**2x1**	**3x1**	**4x1**	**5x1**	**6x1**	**12x1**	**18x1**	**24x1**	**36x1**	**48x1**	**60x1**
Risk premium	3.53 (4.52)	4.91 (4.52)	5.74 (4.52)	6.32 (4.52)	6.81 (4.52)	7.34 (4.52)	8.72 (4.52)	9.32 (4.52)	9.78 (4.52)	11.27 (4.52)	12.15 (4.52)	12.44 (4.52)
Market timing	3.87 (2.59)	3.34 (1.96)	3.07 (1.76)	2.31 (1.28)	2.67 (1.41)	3.16 (1.76)	3.54 (1.68)	1.73 (0.86)	0.11 (0.07)	-0.15 (-0.16)	-0.03 (-0.05)	-0.05 (-0.06)
Net Long	21.74 (7.28)	30.18 (9.58)	35.31 (11.01)	38.89 (12.27)	41.88 (13.37)	45.14 (14.71)	53.65 (16.23)	57.31 (18.11)	60.17 (22.30)	69.34 (39.79)	74.71 (51.03)	76.51 (48.80)

Panel A of Table 4.5. reveals that seven of the TSAlt NE=0 strategies significantly exceed their original time-series counterparts (TS NE=0). When considered on a Sharpe ratio risk-adjusted basis however, only two of the TSAlt NE=0 strategies outperform the original WML strategies, with five exhibiting insignificant differences in returns and the remaining five underperforming. As such, based on zero net investment exposure returns, the TSAlt NE=0 method for time-series momentum provides strong relative performance but little improvement on the originally specified, TS NE=0 technique.

However, Panel B substantially contradicts Panel A. When calculating the TSAlt NE=variable returns, the approach produces returns superior to the original TS NE=variable counterpart for every tested formation period. This finding is true on both an absolute return account and on a risk-adjusted account. The alternative approach therefore warrants further investigation in future studies so as to identify the optimal threshold for asset selection.

This study however continues to look at the 12x1 base-case strategy. The TSAlt NE=0 time-series strategy generates insignificant differences in returns when compared to the original approach. Lower returns to the winner portfolio (0.75% p.a., t-statistic = 1.19), higher returns to the loser portfolio (0.65% p.a., t-statistic = 0.36), and resultant lower returns to the WML portfolio (1.38% p.a., t-statistic = 0.76) are economically unfavourable to the trader, but insignificant by statistical analysis. Additionally, although Panel B shows that the TSAlt NE=variable approach economically outperforms the TS NE=variable counterpart, this outperformance too is statistically insignificant (2.17% p.a., t-statistic = 1.44). Even on a risk-adjusted basis, a Sharpe ratio of 1.51 does not constitute a statistically significant improvement on the 1.43 attributed to the original TS NE=variable approach.

Panel C of Table 4.5. provides the TSAlt NE=variable equivalent of the induced components of time-series momentum, as seen in sub-chapter 4.2. Unsurprisingly, given that the TSAlt NE=variable strategy requires a considerably lower rate of return from stocks in order to be classified as past winners, the approach experiences significantly larger net long positions for every tested formation period. Again unsurprisingly, given that the risk premium component is a function of the average net long position (and the same equally-weighted index), the alternative approach yields significantly larger risk premiums for all formation periods.

The alternative approach also yields superior market timing returns on the extreme ends of the formation period spectrum, although these too are insignificant. The only significant market timing returns are earned by the 1x1 (t-statistic = 2.59) and 2x1 (t-statistic = 1.96) strategies, thus confirming the short-term results of the original approach. Finally, the 12x1 TSAlt NE=variable base-case achieves a risk premium of 2.68% per annum higher than the corresponding standard time-series strategy (t-statistic = 4.52), with 16.50% more of the portfolio long (t-statistic = 20.86). Neither of the two strategies TS NE=variable nor TSAlt NE=variable achieve significant market timing returns.

4.4. Momentum crash results

Table 4.6. presents the skewness of each of the 12x1 momentum strategies previously examined in this report to identify whether any of the strategies experienced significant momentum crashes over the period 2002.02-2015.05. These strategies were in general found to exhibit the best Sharpe ratios throughout this report, and as such are reasonable base-case candidates for market use.

Table 4.6.: Skewness of 12x1 momentum strategies, 2002.02-2015.05

This table presents the realised skewness of returns of each of the six 12x1 momentum strategies previously examined in this report: the top decile minus bottom decile cross-sectional strategy (CS deciles), the top half minus bottom half cross-sectional strategy (CS halves), the investment-neutral time-series strategy (TS NE=0), the variable investment exposure time-series strategy (TS NE=variable), the zero absolute threshold investment-neutral time-series strategy (TSAlt NE=0) and the zero absolute threshold variable exposure time-series strategy (TSAlt NE=variable). All strategies' skewness is presented over the period 2002.02-2015.05. Figures in brackets are Z-statistics. See Appendix E1 for the full strategy spectrum's skewness.

	CS deciles	**CS halves**	**TS NE=0**	**TS NE=variable**	**TSAlt NE=0**	**TS Alt NE=variable**
Skewness	-0.41 (-2.12)	-0.72 (-3.74)	-0.57 (-2.96)	0.26 (1.35)	-0.89 (-4.62)	0.05 (0.26)

Of the tested 12x1 strategies, all of the investment-neutral approaches experience significant negative skewness of returns. As seen in the literature, this would imply that employing a 12x1 investment-neutral momentum strategy, whether time-series or cross-sectional, results in momentum crash events. The two 12x1 time-series strategies with non-zero net investment exposures (TS NE = variable TSAlt NE=variable) are insignificantly positively skewed and thus deemed free of sustained multi-period momentum losses. This finding is only true of these two strategies for short- to medium-term formation period strategies, while longer-term strategies exhibit significant negative skewness (see Appendix D1). Figure 4.4. graphically illustrates the first two points by presenting the trends of the cumulative returns to each of the six 12x1 strategies.

Figure 4.4.: Cumulative return trends – 12x1 strategies, 2002.02-2015.05

This figure plots the trends of the cumulative returns to the six 12x1 momentum strategies over the period 2002.02-2015.05. Panel A: the cross-sectional top decile minus bottom decile strategy (CS deciles), Panel B: the cross-sectional top half minus bottom half strategy (CS halves), Panel C: the investment-neutral time-series strategy (TS NE=0), Panel D: the investment-neutral zero absolute threshold time-series strategy (TSAlt NE=0), Panel E: the variable exposure time-series strategy (TS NE=variable), and Panel F: the variable exposure zero absolute threshold time-series strategy (TSAlt NE=variable).

The steep downward trends observed over the central areas of Panels A, B, C, and D of Figure 4.4. confirm the existence of extreme momentum losses to zero investment strategies, over sustained periods of time. Panels E and F however show no signs of this trend in cumulative returns. This lack of downward trend in conjunction with the insignificant skewness of returns show evidence that strategies of the non-zero investment exposure sort are absent of momentum crashes. The absence of crashes in these strategies is likely a function of the strategies' ability to hold long (short) positions in stocks when the market rises (declines) – allowing the strategy to benefit from the risk premium derived in sub-chapter 4.2. (Eq. 5). Figure 4.5. illustrates this point by plotting the 12x1 TS NE=variable strategy's net long exposure against the monthly return to the equally-weighted index.

Figure 4.5.: Time-varying net long exposure – 12x1 TS NE=variable strategy, 2002.02-2015.05

This figure plots the 12x1 variable net investment exposure time-series (TS NE=variable) strategy's monthly net long exposure to the market against the monthly return to the equally-weighted index (EW Index). The net long and EW Index returns are both in percent.

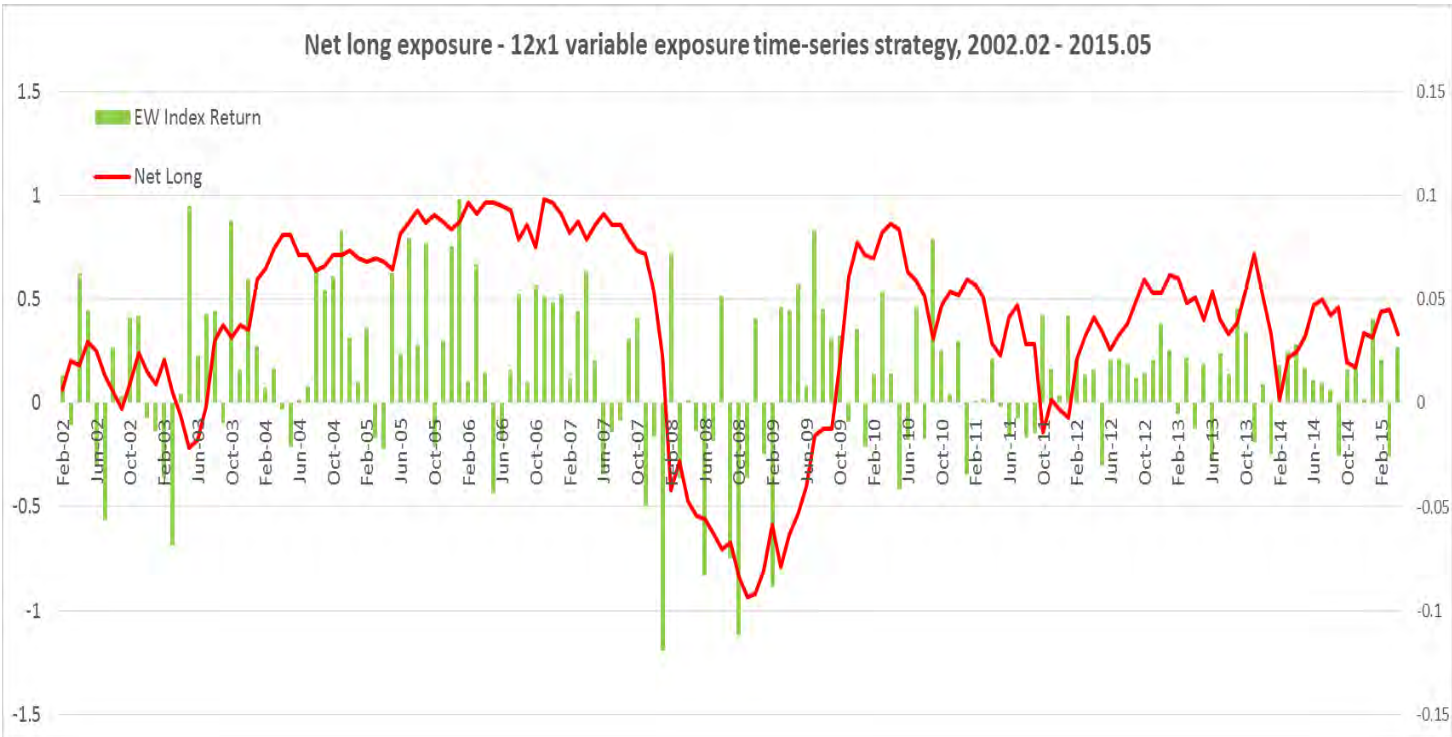
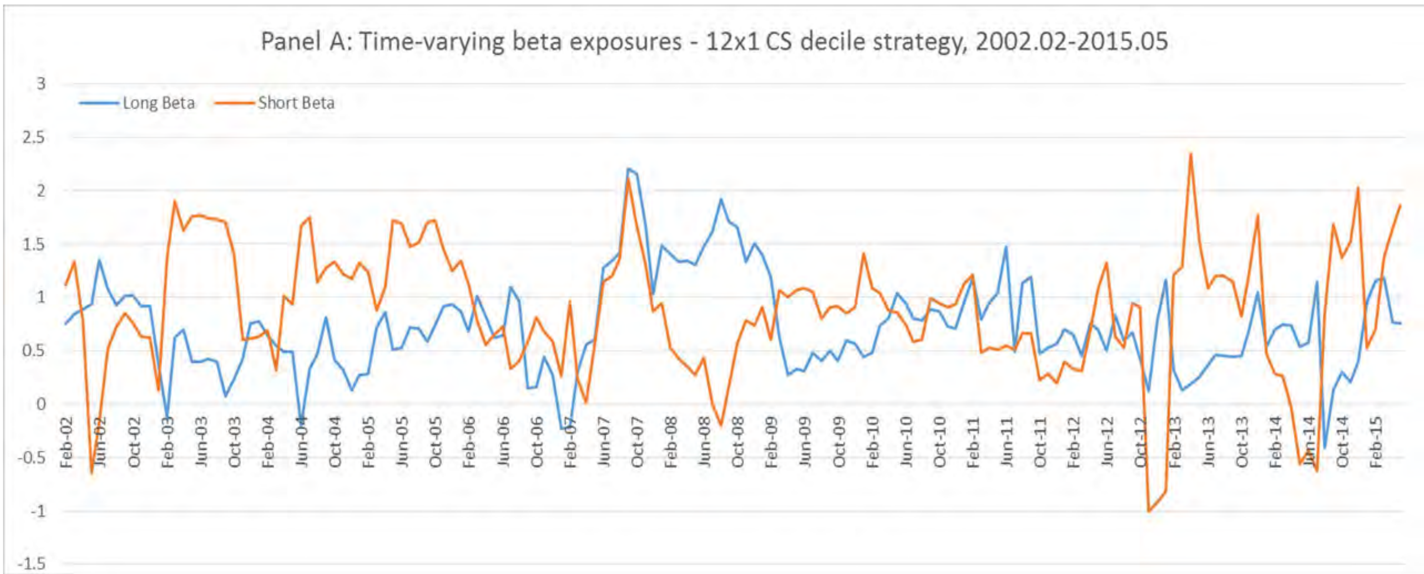


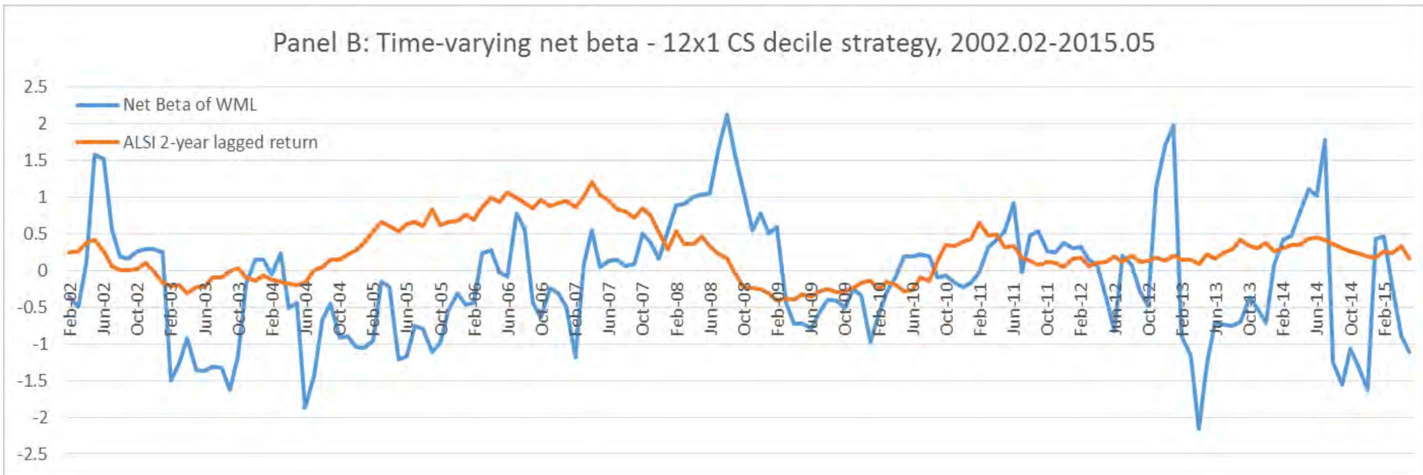
Figure 4.5. illustrates one of the strong reasons as to why the 12x1 TS NE=variable strategy experiences insignificant skewness of returns and no crash events. Over most of the period, the 12x1 TS NE=variable strategy takes time-varying net long positions in the market of the same sign as the return to the EW Index. As such the strategy earns the return to the market (the EW index in this case) multiplied by the net exposure to the market – the risk premium. Over the investment-neutral down-trend period (Panels A, B, C, and D of Figure 4.4.), the TS NE=variable is generally net short in the market when the EW index earns negative returns (2008.08-2009.06: average net long = -73.17%, average EW Index return = -1.64% p.m.) thus earning positive returns even under stressed market

conditions. This is in stark contrast to the zero investment exposure strategies (CS deciles, CS halves, TS NE=0, and TSAlt NE=0) which, as the name suggests, experience no net long exposure and as such do not earn the market-linked return. In addition to the time-varying net investment exposures of these two strategies, all six approaches also experience time-varying exposures to the market through their weighted stock betas. Figure 4.6. presents the 6-month rolling betas of the long winner and short loser portfolios for the 12x1 decile cross-sectional momentum strategy, to illustrate this point.

Figure 4.6.: Time-varying beta exposure – 12x1 CS decile strategy, 2002.02-2015.05 (2008.01-2012.12)

This figure plots the estimated market beta exposures of the 12x1 top decile cross-sectional "past winner" portfolio and 12x1 bottom decile cross-sectional "past loser" portfolio to South Africa's All-Share Index (ALSI). Panel A presents the beta estimates over the full period 2002.02-2015.05. Panel B presents the net beta exposure estimate of the winner minus loser portfolio against the 2-year lagged return on the JSE All-Share Index over the same period. The betas were estimated using a 6-month rolling regression of the excess returns to the portfolios against the excess returns on the ALSI.





Similar to the literature, Panel A of Figure 4.6. shows that both the long and short betas fluctuate markedly over the full sample, with the short beta making marginally more extreme moves than the long. Through this period, two crash scenarios occurred – as defined by the literature. Over August 2008 to October 2008, the 12x1 CS deciles approach earned cumulative losses of 44.71% (14.90% p.m. over three months). In contrast to the literature's crash cases however, this strategy held positive net beta exposure to the market in all three months (Panel B). Additionally, where the literature found a large majority of momentum losses to occur on a market upswing following a lagged two year downtrend, this crash period experienced market returns of 0.31%, -13.24%, and -11.65% for August, September, and October respectively. As such, the strategy was positively exposed to the negative turn in JSE ALSI returns thereby resulting in negative gains.

Six months following, the same strategy earned further cumulative losses of 48.43% (12.11% p.m. over four months). More closely to the literature, these losses occurred in months when the JSE ALSI had declined over the preceding 24-months, and corrected; May 2009 (10.33%). Again, similar to the literature, the strategy held substantial negative net beta exposure to the JSE ALSI over these three months. This net exposure was due to the low long beta (Apr-09: 0.27, May-09: 0.33, Jun-09: 0.31) compared to the short beta (Apr-09: 1.00, May-09: 1.07, Jun-09: 1.09). As such the position was negatively exposed to the positive swing in JSE ALSI returns, again resulting in negative gains. These two crash scenarios are easily observable in Figure 4.7.

Figure 4.7. Cumulative returns to the 12x1 decile cross-sectional strategy, 2002.02-2015.05

This figure plots the cumulative returns over the period 2002.02-2015.05 for the 12x1 top decile "past winner" portfolio, the 12x1 bottom decile "past loser" portfolio and the net investment-neutral 'winner minus loser' portfolio. This plot assumes a R1 investment in the "past winner" and "past loser" portfolios over each month, beginning in February 2002. Both the top decile's and bottom decile's returns are presented net of the risk-free rate of return.

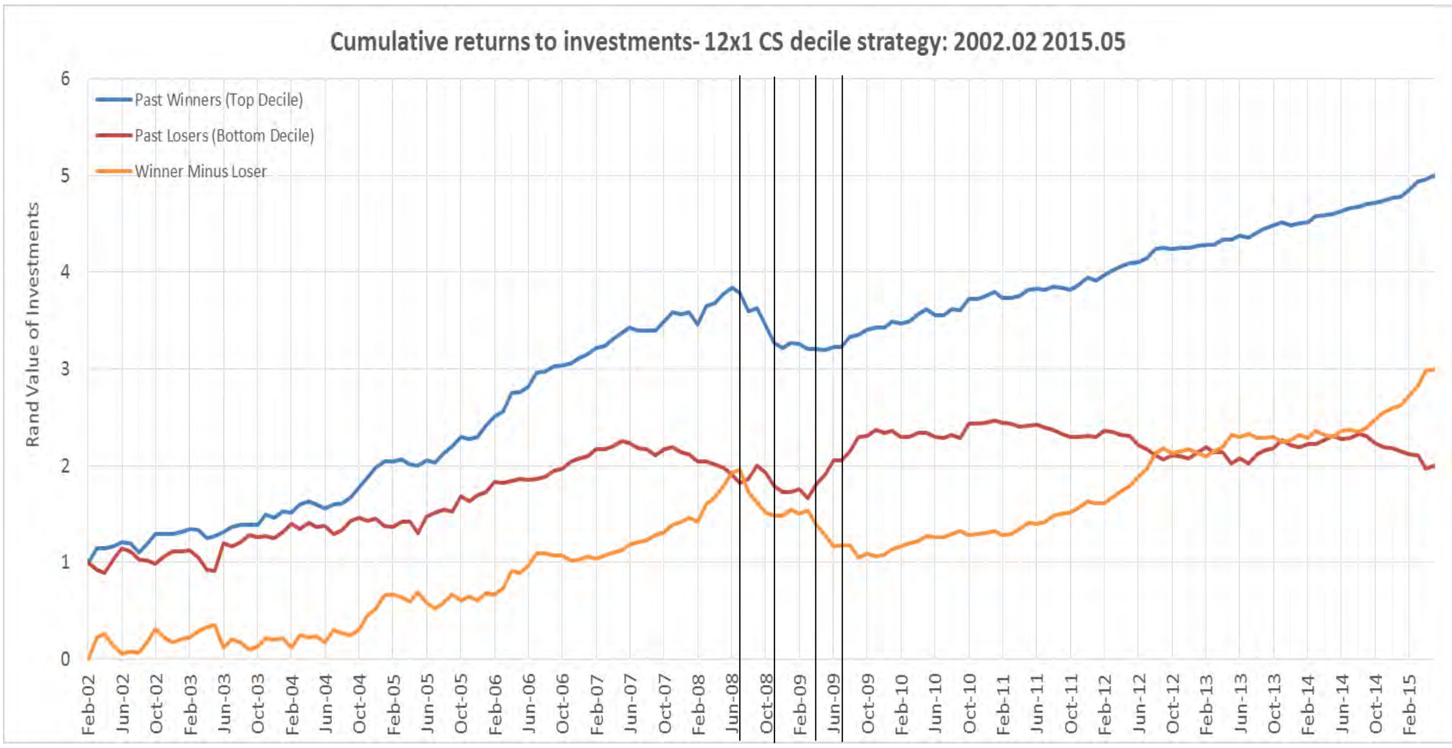


Figure 4.7. clearly demonstrates the two momentum crashes mentioned above. Over the first crash of 2008.08-2008.10, it is evident that a significant portion of the WML losses are attributable to the downturn in the long winner portfolio (-33.89%, -11.30% p.m). The long winner portfolio eventually bottoms-out in 2008.12 after losing 57.54% in five months. Conversely, the short loser portfolio actually gains 10.82% over the three crash months (3.61% p.m.) resulting in losses of 23.46%, 10.04%, and 11.22% over 2008.08-2008.10. In the subsequent crash months, the reverse is true. The long winner portfolio gains on average 0.90% per month (2.71% total) over April 2009 to June 2009 when the short loser averages gains of 13% (39% total), resulting in a WML loss of 36.29% over three months (-12.10% per month).

This is clear evidence of Daniel and Moskowitz's (2013) loser portfolio crashing over the winner portfolio. Evidently, momentum profits recover over the subsequent 24-months, with the strategy continuing to make strong returns. Extremely similar results are found for the 12x1 CS halves strategy (Appendix B2i), the 12x1 TS NE=0 strategy (Appendix B3i) and the 12x1 TSAlt NE=0 strategy (Appendix B3ii), in terms of the cumulative gains and losses in crash scenarios. All four approaches confirm that the first crash occurred as a result of the long winner portfolio crashing down, whilst the second follows the literature whereby the short loser portfolio crashes up above the long winner.

Interestingly, although the crash losses of the 18x1 and 6x1 CS deciles strategies are observably lower than those of the 12x1 strategy over the three months, the 18x1 and 6x1 experienced the crashes over longer sustained periods – resulting in losses accumulated over more time. Where the 12x1 CS decile strategy's winner portfolio crashed over August 2008 to October 2008 for the first crash, the 18x1 CS decile approach's winner portfolio fell in value over August 2008 to May 2009 (Appendix B1ii). The 6x1 CS deciles approach, although the same as the 12x1 approach in the first crash, experienced an extended past loser crash up from April 2009 to November 2009 instead of the 12x1's April to June crash (Appendix B1iii). The 18x1 approach's loser portfolio crashed up a further two months into January 2010. These findings both show that although significantly crash loss earning, the 12x1 CS deciles approach minimises the length of time over which these losses occur in comparison to other CS deciles strategies.

5. Conclusions

Over the full 2002.02-2015.05 sample period, this report shows that there is consistently strong and significant return predictability in stocks listed on the JSE. As such there is ample profit to be made by entering into a stock momentum strategy – a bet that stocks' past returns are indicative of its future returns. This appears to be overwhelmingly true for the majority of momentum strategies tested over the period.

By entering into a 12-month formation period, 1-month holding period (12x1) top decile minus bottom decile cross-sectional momentum strategy (CS deciles) – a strategy that goes long (short) in stocks that outperformed (underperformed) its peers over the formation period, betting that this trend will continue – a trader is able to earn 22.63% per annum on average when investment-neutral, and average excess returns up to 30.21% per annum per South African rand long in the strategy. This constitutes significant outperformance of the SWIX ALSI benchmark, which achieves returns of 10.30% per annum per rand long invested. The same strategy thus also pays 7.58% excess returns per annum on average per rand in the short side. As such the short side of the strategy simply affords the trader a method for funding the long investment.

Much like the decile cross-sectional strategies, the top half minus bottom half cross-sectional strategies (CS halves) exhibit 'short straddle-like' returns, with both the short- and long-term formation period strategies being outperformed by the medium-term formation period equivalents. However, the lower variability between the long and short portfolio constituents results in every CS halves strategy being outperformed by the top decile minus bottom decile counterpart. This reduction of variability however also lowers the risk attached to the strategy, although disproportionately to the reduction in returns. Thus over the 2002.02-2015.05 it is always better to invest in a CS deciles strategy than a CS halves momentum strategy.

Both of the strategies however exhibit significant leftward skewness of returns due to their uncommon crash events where the strategies earn large negative returns over successive months. Over the full sample period, two of these events arose for the 12x1 cross-sectional strategies: 2008.08-2008.10 and 2009.04-2009.06. The CS deciles approach earned quarterly losses of 44.71% and 48.43% over these two crash periods. Contra to the literature, the first crash came as a result of the strategy's positive net market beta exposure during a market downturn. The first crash's losses are largely attributed to the long winner portfolio crashing down in all three months.

The second crash however, as with the literature, appeared as a result of the short loser portfolio's positive beta exceeding the beta of the long winner (net negative beta). As such, when the JSE ALSI recovered following a lagged 2-year downtrend, the strategy was again unfavourably exposed to the market's direction. This is further evidence of the literature's short loser crashing up. This may be corrected for in future studies by any of the methods mentioned in sub-chapter 2.3. The 12x1 CS deciles approach does minimises the crash lengths however, when compared to CS deciles approaches our longer and shorter formation periods.

Further, this report analyses the performance a momentum strategy which uses past time-series returns to determine whether a stock is bought or sold. The time-series strategy thus goes long (short) in stocks that achieve positive (negative) excess returns over the formation period, again betting that this trend will continue over the holding period. Two specifications were tested: the net investment exposure-neutral strategy (TS NE=0), and the non-zero net investment strategy (TS NE=variable). A trader would prefer the TS NE=variable strategy to the TS NE=0 strategy for every tested formation period, achieving the best returns of 25.92% per annum to the 12x1 approach. This outperformance is strongly linked to the ability of the strategy to go long (short) in the market when the market earns positive (negative) returns.

The returns to the TS NE=variable approach are broadly made up of four components: the return to the CS halves approach, a risk premium component, a market timing component, and an observed stock selection component. Of the components, only the risk premium is significant for all formation periods – this due to the positive average net long exposure of the strategy earning the positive equally-weighted index return. The market timing component appears to be significant only at short formation periods, while the observed stock selection element is significant at all but the 18-month formation period. Looking at an alternative time-series approach where the long (short) portfolio is made up of stocks with positive (negative) formation period 'raw' returns, the same findings are evident. The variable net exposure zero absolute threshold approach (TS NE=variable) takes larger average long positions in the market and thus the risk premium component is larger and significant for all strategies. The market timing component is again only significant at short formation periods.

Unlike the cross-sectional approaches, the TS NE=variable approach exhibits insignificant skewness of returns unless employed on an investment-neutral basis (TS NE=0). The negligible skewness is attributed to the ability of the strategy to take net long or short market positions and thus earn positive market returns even when the market is under stress. The TS NE=0 strategy however, strongly confirms the crash results as seen by the 12x1 CS deciles approach. The first crash occurs in the TS NE=0 approach due to the long winner crashing down, while the second crash is the same short loser portfolio crashing up as identified by the CS deciles strategy. Even when examining the zero exposure zero threshold time-series approach (TSAlt NE=0), the same crashes characteristics are evident.

Finally, as a practical application, a combined TS NE=0 and CS halves made. The strategy goes long in stocks only if the formation period return exceeds both the cross-sectional average and zero. Thus the approach implements elements from both time-series and cross-sectional momentum on a long-only mandate – a practical momentum strategy employed in industry. The strategy earned returns exactly equal to the original CS halves approach due to the majority of sample months' cross-sectional average return exceeding zero. Thus it is more beneficial to test this strategy over different market conditions – something left to future studies.

The findings of this report present undeniably strong evidence for the profitability of momentum in stocks in South Africa, while also proving the point that the strategies come with high risk of losses. However, this report pays no attention to trading costs – a strong return-mitigating cost. As such any future research in this field would strongly benefit from the inclusion of trading costs associated with the strategies. In rebuttal, in order to have significantly conclusion-altering impacts, the JSE's trading costs would have to exceed substantial returns – a high improbability.

Throughout this report, attention has been drawn to areas for future research and improvement. However, yet to be said is that given that the results of the crash cases proved different to the literature, the implementation of the suggested momentum crash mitigating techniques may prove to be an interesting field for investigation in South African stocks. To these ends, this report opens wide scope for future research into time-series momentum as well as momentum crashes.

Finally, this report acknowledges that for a momentum strategy to be profitable a trader must have the ability to long or short stocks as required at any given time *t*. Given the relative illiquidity of the majority of stocks listed on the JSE, this report may overstate the returns to such a momentum strategy. Future research of momentum is best served by employing such a strategy on a sub-set of this report's data, where stocks are selected with more stringent liquidity constraints.

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Appendix A: Eviews code

A1: Eviews code for cross-sectional momentum portfolios

```
'Single cross-sectional momentum factors are tested on future one month returns here and a table
of metrics produced.

!smplstart=410                    '1994.02
!minmonth=506                     '2002.02
!maxmonth=665
!Totalshares=170
!Totalmonths=(!maxmonth-!minmonth)+1

d CSResults
d mrTopDec
d mrBotDec
d rTopDec
d rBotDec
d obsTopDec
d obsBotDec
d mrTopHalf
d mrBotHalf
d rTopHalf
d rBotHalf
d obsTopHalf
d obsBotHalf

TABLE CSRESULTS
'label the results table

CSresults(2,1)="Average summed CS excess return: Top decile, CS long"
CSresults(3,1)="Average summed CS excess return: Bottom decile, CS short"
CSresults(4,1)="Average summed CS excess return: Top - bottom, CS long-short"
CSresults(5,1)="T-statistic: Average top - bottom summed CS excess long-short return"
```

```
CSresults(6,1)="Average observations: Top decile, CS long"
CSresults(7,1)="Average observations: Bottom decile, CS short"
CSresults(8,1)="Skew of top - bottom CS excess long-short return"
CSresults(9,1)="Standard deviation of top - bottom CS excess long-short return"

CSresults(11,1)="Average CS excess return: Top decile, CS long"
CSresults(12,1)="Average CS excess return: Bottom decile, CS short"
CSresults(13,1)="Average CS excess return: Top - bottom, CS long-short"
CSresults(14,1)="T-statistic: Average top - bottom CS excess long-short return"
CSresults(15,1)="Average observations: Top decile, CS long"
CSresults(16,1)="Average observations: Bottom decile, CS short"
CSresults(17,1)="Skew of top - bottom CS excess long-short return"
CSresults(18,1)="Standard deviation of top - bottom CS excess long-short return"

CSresults(20,1)="Average summed CS excess return: Top half, CS long"
CSresults(21,1)="Average summed CS excess return: Bottom half, CS short"
CSresults(22,1)="Average summed CS excess return: Top half - bottom half, CS long-short"
CSresults(23,1)="T-statistic: Average top half - bottom half summed CS excess long-short return"
CSresults(24,1)="Average observations: Top half, CS long"
CSresults(25,1)="Average observations: Bottom half, CS short"
CSresults(26,1)="Skew of top half - bottom half CS excess long-short return"
CSresults(27,1)="Standard deviation of top half - bottom half CS excess long-short return"

CSresults(29,1)="Average CS excess return: Top half, CS long"
CSresults(30,1)="Average CS excess return: Bottom half, CS short"
CSresults(31,1)="Average CS excess return: Top half - bottom half, CS long-short"
CSresults(32,1)="T-statistic: Average top half - bottom half CS excess long-short return"
CSresults(33,1)="Average observations: Top half, CS long"
CSresults(34,1)="Average observations: Bottom half, CS short"
CSresults(35,1)="Skew of top half - bottom half CS excess long-short return"
CSresults(36,1)="Standard deviation of top half - bottom half CS excess long-short return"

CSresults(38,1)="Average excess return to Shareholder-weighted Index"
CSresults(39,1)="Skew of excess Shareholder-weighted index return"
```

```
CSresults(40,1)="Standard deviation of excess Shareholder-weighted index return"

!num =0

series mrTopDec
series mrBotDec
series rTopDec
series rBotDec
series obsTopDec
series obsBotDec
series mrTopHalf
series mrBotHalf
series rTopHalf
series rBotHalf
series obsTopHalf
series obsBotHalf

'***********
!row=1
!column=1
!col=1

smpl @all

'1. LOOP BY MOMENTUM FACTOR++++++++++++++++++++++

for %0 MOM1 MOM2 MOM3 MOM4 MOM5 MOM6 MOM12 MOM18 MOM24 MOM36 MOM48
MOM60

!column=!column+1

'label row 1 with factor names starting in column 2,
genr t{%0}={%0}
```

```
'2. LOOP BY MONTH++++++++++++++++++++++

for !month=!minmonth to !maxmonth-1

smpl if monthnum=!month

!row=!row+1
'________________CORE: for each momentum factor in each month

smpl if monthnum=!month

genr Top1cut=@quantile({%0},0.90)
genr Bot1cut=@quantile({%0},0.10)

smpl if monthnum=!month and {%0}=>Top1cut
mrTopDec(!month-(!smplstart-1))=@mean(excess_returnfwd1)
obsTopDec(!month-(!smplstart-1))=@obs({%0})
rTopDec(!month-(!smplstart-1))=@sum(excess_returnfwd1)

smpl if monthnum=!month and {%0}<Bot1cut
mrBotDec(!month-(!smplstart-1))=@mean(excess_returnfwd1)
obsBotDec(!month-(!smplstart-1))=@obs({%0})
rBotDec(!month-(!smplstart-1))=@sum(excess_returnfwd1)

'get back to prior smpl after above filtering

smpl if monthnum=!month

'repeat logic for top and bot halves

genr HalfCut=@quantile({%0},0.50)

smpl if monthnum=!month and {%0}=>HalfCut
mrTopHalf(!month-(!smplstart-1))=@mean(excess_returnfwd1)
```

```
obsTopHalf(!month-(!smplstart-1))=@obs({%0})
rTopHalf(!month-(!smplstart-1))=@sum(excess_returnfwd1)

smpl if monthnum=!month and {%0}<HalfCut
mrBotHalf(!month-(!smplstart-1))=@mean(excess_returnfwd1)
obsBotHalf(!month-(!smplstart-1))=@obs({%0})
rBotHalf(!month-(!smplstart-1))=@sum(excess_returnfwd1)

'get back to prior smpl after above filtering
smpl if monthnum=!month

'_________________________END OF CORE
next
'month loop
'after the inner month loop is finished the results for the factor are put into the results table

smpl @all

!col=!col+1

CSresults(1,!col)=%0
CSresults(2,!col)=@mean(rTopDec)
CSresults(3,!col)=@mean(rBotDec)
CSresults(4,!col)=@mean(rTopDec)-@mean(rBotDec)
CSresults(5,!col)=@mean(rTopDec-rBotDec)*(!Totalmonths^0.5)/@stdev(rTopDec-rBotDec)
CSresults(6,!col)=@mean(obsTopDec)
CSresults(7,!col)=@mean(obsBotDec)
CSresults(8,!col)=@skew(rTopDec-rBotDec)
CSresults(9,!col)=@stdev(rTopDec-rBotDec)

CSresults(11,!col)=@mean(mrTopDec)
CSresults(12,!col)=@mean(mrBotDec)
CSresults(13,!col)=@mean(mrTopDec)-@mean(mrBotDec)
```

```
CSresults(14,!col)=@mean(mrTopDec-mrBotDec)*(!Totalmonths^0.5)/@stdev(mrTopDec-
mrBotDec)
CSresults(15,!col)=@mean(obsTopDec)
CSresults(16,!col)=@mean(obsBotDec)
CSresults(17,!col)=@skew(mrTopDec-mrBotDec)
CSresults(18,!col)=@stdev(mrTopDec-mrBotDec)

CSresults(20!col)=@mean(rTopHalf)
CSresults(21,!col)=@mean(rBotHalf)
CSresults(22,!col)=@mean(rTopHalf)-@mean(rBotHalf)
CSresults(23,!col)=@mean(rTopHalf-rBotHalf)*(!Totalmonths^0.5)/@stdev(rTopHalf-rBotHalf)
CSresults(24,!col)=@mean(obsTopHalf)
CSresults(25,!col)=@mean(obsBotHalf)
CSresults(26,!col)=@skew(rTopHalf-rBotHalf)
CSresults(27,!col)=@stdev(rTopHalf-rBotHalf)

CSresults(29,!col)=@mean(mrTopHalf)
CSresults(30,!col)=@mean(mrBotHalf)
CSresults(31,!col)=@mean(mrTopHalf)-@mean(mrBotHalf)
CSresults(32,!col)=@mean(mrTopHalf-mrBotHalf)*(!Totalmonths^0.5)/@stdev(mrTopHalf-
mrBotHalf)
CSresults(33,!col)=@mean(obsTopHalf)
CSresults(34,!col)=@mean(obsBotHalf)
CSresults(35,!col)=@skew(mrTopHalf-mrBotHalf)
CSresults(36,!col)=@stdev(mrTopHalf-mrBotHalf)

CSresults(38,!col)=@mean(excess_swix_alsi_returns)
CSresults(39,!col)=@skew(excess_swix_alsi_returns)
CSresults(40,!col)=@stdev(swix_alsi_returns)

d t{%0}
next
'end of factor (outer) loop
```

A2: EViews code for time-series momentum portfolios

```
'Single time-series momentum factors are tested on future one month returns and a table of metrics
is produced.

!smplstart=410                          '1994.02
!minmonth=506                           '2002.02
!maxmonth=665
!totalshares=170
!totalmonths=(!maxmonth-!minmonth)+1

d TSResults
d mt
d mrTop
d mrBot
d rTop
d rBot
d obsTop
d obsBot
d EW
d rts
d netLongPosition

TABLE TSRESULTS
'label the results table

TSresults(2,1)="Average summed TS return, TS long"
TSresults(3,1)="Average summed TS return, TS short"
TSresults(4,1)="Average summed TS return, TS long-short"
TSresults(5,1)="T-statistic: Average summed TS long-short return"
TSresults(6,1)="Standard deviation of TS long-short return"

TSresults(8,1)="Average observations, TS long"
TSresults(9,1)="Average observations, TS short"
TSresults(10,1)="Average net long, TS long-short"
```

```
TSresults(11,1)="Correlation: Net long, EW"
TSresults(12,1)="Risk premium: Average net long * average EW"
                                        'Risk premium - Goyal & Jegadeesh (2015)
TSresults(13,1)="Market timing: average(net long-average net long) * EW"
                                        'Market timing - Goyal & Jegadeesh (2015)
TSresults(14,1)="Average return to TS strategy (Goyal & Jegadeesh, 2015)"
                                        'Zero net exposure by design: $1 short and $1 long
TSresults(15,1)=”Standard deviation of TS strategy”
TSresults(16,1)=”T-statistic: Average TS strategy return”
TSresults(17,1)="Skew of TS strategy"
TSresults(18,1)="Average TS return, TS long"
TSresults(19,1)="Average TS return, TS short"
TSresults(20,1)="Average TS return, TS long-short"
TSresults(21,1)="T-statistic: Average TS long-short return"
TSresults(22,1)="Standard deviation of TS long-short return”
TSresults(23,1)=”Skew of TS long-short return”
TSresults(24,1)="Average excess return to Shareholder-weighted Index"
TSresults(25,1)="Skew of excess Shareholder-weighted index return"
TSresults(26,1)="Standard deviation of excess Shareholder-weighted index return"

!num = 0

series mt                               'market timing
series mrTop                            'mean return to long stocks
series mrBot                            'mean return to short stocks
series rTop                             'return to long stocks
series rBot                             'return to short stocks
series obsTop                           'no. of observations above threshold
series obsBot                           'no. of observations below threshold
series EW                               'equally-weighted index
series rts                              'returns to time-series
series netLongPosition                  'proportion netLong

'***********
```

```
!row=1
!column=1
!col=1

smpl @all

'1. LOOP BY MOMENTUM FACTOR++++++++++++++++++++++

for %0 excess_MOM1 excess_MOM2 excess_MOM3 excess_MOM4 excess_MOM5 excess_MOM6
excess_MOM12 excess_MOM18 excess_MOM24 excess_MOM36 excess_MOM48 excess_MOM60

!column=!column+1

'label row 1 with factor names starting in column 2
genr t{%0}={%0}

'2. LOOP BY MONTH++++++++++++++++++++++

for !month=!minmonth to !maxmonth-1
'maxmonth-1 is because in the last month there are no returnfwd1

smpl if monthnum=!month
'________________CORE: for momentum factor in each month

EW(!month-(!smplstart-1))=@mean(excess_returnfwd1)

smpl if monthnum=!month and {%0}=>0                    'Excess mom=>0
rTop(!month-(!smplstart-1))=@sum(excess_returnfwd1)
obsTop(!month-(!smplstart-1))=@obs({%0})
mrTop(!month-(!smplstart-1))=@mean(excess_returnfwd1)

smpl if monthnum=!month and {%0}<0                     'Excess mom<0
rBot(!month-(!smplstart-1))=@sum(excess_returnfwd1)
obsBot(!month-(!smplstart-1))=@obs({%0})
```

```
mrBot(!month-(!smplstart-1))=@mean(excess_returnfwd1)


'get back to prior smpl after above filtering
smpl if monthnum=!month
netLongPosition(!month-(!smplstart-1)) = (obsTop(!month-(!smplstart-1))-obsBot(!month-
(!smplstart-1)))/(obsTop(!month-(!smplstart-1))+obsBot(!month-(!smplstart-1)))

'_________________________END OF CORE
next

'month loop
'after the inner month loop is finished the results for the factor are put into the TSresults table

smpl @all

genr rts=(2/(obsTop+obsBot))*(rTop-rBot)                'Goyal & Jegadeesh (2015)
genr mt=(netLongPosition-@mean(netLongPosition))*EW     'Goyal & Jegadeesh (2015)

!col=!col+1

TSresults(1,!col)=%0
TSresults(2,!col)=@mean(rTop)
TSresults(3,!col)=@mean(rBot)
TSresults(4,!col)=@mean(rTop)-@mean(rBot)
TSresults(5,!col)=(@mean(rTop)-
@mean(rBot))*!Totalmonths^0.5/((@stdev(rTop))^2+(@stdev(rBot))^2-
2*@stdev(rTop)*@stdev(rBot)*@cor(rTop,rBot))^0.5
TSresults(6,!col)=((@stdev(rTop))^2+(@stdev(rBot))^2-
2*@stdev(rTop)*@stdev(rBot)*@cor(rTop,rBot))^0.5
TSresults(8,!col)=@mean(obsTop)
TSresults(9,!col)=@mean(obsBot)
TSresults(10,!col)=@mean(netLongPosition)
TSresults(11,!col)=@cor(netLongPosition,EW)
```

```
TSresults(12,!col)=@mean(netLongPosition)*@mean(EW)
TSresults(13,!col)=@mean(mt)
TSresults(14,!col)=@mean(rts)
TSresults(15,!col)=@stdev(rts)
TSresults(16,!col)=(@mean(rts)*!Totalmonths^0.5)/@stdev(rts)
TSresults(17,!col)=@skew(rts)
TSresults(18,!col)=@mean(mrTop)
TSresults(19,!col)=@mean(mrBot)
TSresults(20,!col)=@mean(mrTop)-@mean(mrBot)
TSresults(21,!col)=(@mean(mrTop)-
@mean(mrBot))*!Totalmonths^0.5/((@stdev(mrTop))^2+(@stdev(mrBot))^2 -
2*@stdev(mrTop)*@stdev(mrBot)*@cor(mrTop,mrBot))^0.5
TSresults(22,!col)=((@stdev(mrTop))^2+(@stdev(mrBot))^2 -
2*@stdev(mrTop)*@stdev(mrBot)*@cor(mrTop,mrBot))^0.5
TSresults(23,!col)=@skew(mrTop-mrBot)
TSresults(24,!col)=@mean(excess_swix_alsi_returns)
TSresults(25,!col)=@skew(excess_swix_alsi_returns)
TSresults(26,!col)=@stdev(swix_alsi_returns)

d t{%0}
next
'end of factor (outer) loop
```

A3: EViews code for zero return threshold time-series momentum portfolios

```
'Single alternative threshold time-series momentum factors are tested on future one month returns
and a table of metrics is produced.

!smplstart=410                    '1994.02
!minmonth=506                     '2002.02
!maxmonth=665
!totalshares=170
!totalmonths=(!maxmonth-!minmonth)+1

d TSAltResults
d mt
d mrTop
d mrBot
d rTop
d rBot
d obsTop
d obsBot
d EW
d rts
d netLongPosition

TABLE TSALTRESULTS
'label the results table

TSALTresults(2,1)="Average summed TS return, TS long"
TSALTresults(3,1)="Average summed TS return, TS short"
TSALTresults(4,1)="Average summed TS return, TS long-short"
TSALTresults(5,1)="T-statistic: Average summed TS long-short return"
TSALTresults(6,1)="Standard deviation of TS long-short return"

TSALTresults(8,1)="Average observations, TS long"
TSALTresults(9,1)="Average observations, TS short"
```

```
TSALTresults(10,1)="Average net long, TS long-short"
TSALTresults(11,1)="Correlation: Net long, EW"
TSALTresults(12,1)="Risk premium: Average net long * average EW"
                                                            'Risk premium - Goyal & Jegadeesh (2015)
TSALTresults(13,1)="Market timing: average(net long-average net long) * EW"
                                                    'Market timing - Goyal & Jegadeesh (2015)
TSALTresults(14,1)="Average return to TS strategy (Goyal & Jegadeesh, 2015)"
                                                    'Zero net exposure by design: $1 short and $1 long
TSALTresults(15,1)="Standard deviation of TS strategy"
TSALTresults(16,1)="T-statistic: Average TS strategy return"
TSALTresults(17,1)="Skew of TS strategy"
TSALTresults(18,1)="Average TS return, TS long"
TSALTresults(19,1)="Average TS return, TS short"
TSALTresults(20,1)="Average TS return, TS long-short"
TSALTresults(21,1)="T-statistic: Average TS long-short return"
TSALTresults(22,1)="Standard deviation of TS long-short return"
TSALTresults(23,1)="Skew of TS long-short return"
TSALTresults(24,1)="Average excess return to Shareholder-weighted Index"
TSALTresults(25,1)="Skew of excess Shareholder-weighted index return"
TSALTresults(26,1)="Standard deviation of excess Shareholder-weighted index return"

!num = 0

series mtALT                                'market timing
series mrTopALT                             'mean return to long stocks
series mrBotALT                             'mean return to short stocks
series rTopALT                              'return to long stocks
series rBotALT                              'return to short stocks
series obsTopALT                            'no. of observations above threshold
series obsBotALT                            'no. of observations below threshold
series EW                                   'equally-weighted index
series rtsALT                               'returns to time-series
series netLongPositionALT                   'proportion netLong
```

```
'***********
!row=1
!column=1
!col=1

smpl @all

'1. LOOP BY MOMENTUM FACTOR++++++++++++++++++++++

for %0 MOM1 MOM2 MOM3 MOM4 MOM5 MOM6 MOM12 MOM18 MOM24 MOM36 MOM48
MOM60

!column=!column+1

'label row 1 with factor names starting in column 2
genr t{%0}={%0}

'2. LOOP BY MONTH++++++++++++++++++++++

for !month=!minmonth to !maxmonth-1
'maxmonth-1 is because in the last month there are no returnfwd1

smpl if monthnum=!month
'________________CORE: for momentum factor in each month

EW(!month-(!smplstart-1))=@mean(excess_returnfwd1)

smpl if monthnum=!month and {%0}=>0                    'Excess mom=>0
rTopALT(!month-(!smplstart-1))=@sum(excess_returnfwd1)
obsTopALT(!month-(!smplstart-1))=@obs({%0})
mrTopALT(!month-(!smplstart-1))=@mean(excess_returnfwd1)

smpl if monthnum=!month and {%0}<0                     'Excess mom<0
rBotALT(!month-(!smplstart-1))=@sum(excess_returnfwd1)
```

```
obsBotALT(!month-(!smplstart-1))=@obs({%0})
mrBotALT(!month-(!smplstart-1))=@mean(excess_returnfwd1)


'get back to prior smpl after above filtering
smpl if monthnum=!month
netLongPositionALT(!month-(!smplstart-1)) = (obsTopALT(!month-(!smplstart-1))-
obsBotALT(!month-(!smplstart-1)))/(obsTopALT(!month-(!smplstart-1))+obsBotALT(!month-
(!smplstart-1)))

'_________________________END OF CORE
next

'month loop
'after the inner month loop is finished the results for the factor are put into the TSALTresults table

smpl @all

genr rtsALT=(2/(obsTopALT+obsBotALT))*(rTopALT-rBotALT)          'Goyal & Jegadeesh (2015)
genr mtALT=(netLongPositionALT-@mean(netLongPositionALT))*EW     'Goyal & Jegadeesh (2015)

!col=!col+1

TSALTresults(1,!col)=%0
TSALTresults(2,!col)=@mean(rTopALT)
TSALTresults(3,!col)=@mean(rBotALT)
TSALTresults(4,!col)=@mean(rTopALT)-@mean(rBotALT)
TSALTresults(5,!col)=(@mean(rTopALT)-
@mean(rBotALT))*!Totalmonths^0.5/((@stdev(rTopALT))^2+(@stdev(rBotALT))^2-
2*@stdev(rTopALT)*@stdev(rBotALT)*@cor(rTopALT,rBotALT))^0.5
TSALTresults(6,!col)=((@stdev(rTopALT))^2+(@stdev(rBotALT))^2-
2*@stdev(rTopALT)*@stdev(rBotALT)*@cor(rTopALT,rBotALT))^0.5
TSALTresults(8,!col)=@mean(obsTopALT)
TSALTresults(9,!col)=@mean(obsBotALT)
```

```
TSALTresults(10,!col)=@mean(netLongPositionALT)
TSALTresults(11,!col)=@cor(netLongPositionALT,EW)
TSALTresults(12,!col)=@mean(netLongPositionALT)*@mean(EW)
TSALTresults(13,!col)=@mean(mtALT)
TSALTresults(14,!col)=@mean(rtsALT)
TSALTresults(15,!col)=@stdev(rtsALT)
TSALTresults(16,!col)=(@mean(rtsALT)*!Totalmonths^0.5)/@stdev(rtsALT)
TSALTresults(17,!col)=@skew(rtsALT)
TSALTresults(18,!col)=@mean(mrTopALT)
TSALTresults(19,!col)=@mean(mrBotALT)
TSALTresults(20,!col)=@mean(mrTopALT)-@mean(mrBotALT)
TSALTresults(21,!col)=(@mean(mrTopALT)-
@mean(mrBotALT))*!Totalmonths^0.5/((@stdev(mrTopALT))^2+(@stdev(mrBotALT))^2 -
2*@stdev(mrTopALT)*@stdev(mrBotALT)*@cor(mrTopALT,mrBotALT))^0.5
TSALTresults(22,!col)=((@stdev(mrTopALT))^2+(@stdev(mrBotALT))^2 -
2*@stdev(mrTopALT)*@stdev(mrBotALT)*@cor(mrTopALT,mrBotALT))^0.5
TSALTresults(23,!col)=@skew(mrTopALT-mrBotALT)
TSALTresults(24,!col)=@mean(excess_swix_alsi_returns)
TSALTresults(25,!col)=@skew(excess_swix_alsi_returns)
TSALTresults(26,!col)=@stdev(swix_alsi_returns)

d t{%0}
next
'end of factor (outer) loop
```

A4: EVIEWS CODE FOR TIME-VARYING BETA EXPOSURES

```
d mlongCSdecBeta
d mshortCSdecBeta
d mlongCShalfBeta
d mshortCShalfBeta
d mlongTSBeta
d mshortTSBeta
d mlongTSALTBeta
d mshortTSALTBeta
d TSBeta
d TSALTBeta

series mlongCSdecBeta
series mshortCSdecBeta
series mlongCShalfBeta
series mshortCShalfBeta
series mlongTSBeta
series mshortTSBeta
series mlongTSALTBeta
series mshortTSALTBeta
series TSBeta
series TSALTBeta

for !month = 0 to 159                                   '2002.02 to 2015.05
smpl 2002.02 + (!month-5) 2002.02 + !month
ls mrTopDec c excess_ALSI_return
mlongCSdecBeta((!month+506)-(!smplstart-1)) = c(2)      '2nd coefficient
ls mrBotDec c excess_ALSI_return
mshortCSdecBeta((!month+506)-(!smplstart-1)) = c(2)     '2nd coefficient
ls mrTopHalf c excess_ALSI_return
mlongCShalfBeta((!month+506)-(!smplstart-1)) = c(2)     '2nd coefficient
ls mrBotHalf c excess_ALSI_return
mshortCSHalfBeta((!month+506)-(!smplstart-1)) = c(2)    '2nd coefficient
```

```
ls mrTop c excess_ALSI_return
mlongTSBeta((!month+506)-(!smplstart-1)) = c(2)          '2nd coefficient
ls mrBot c excess_ALSI_return
mshortTSBeta((!month+506)-(!smplstart-1)) = c(2)         '2nd coefficient
ls rts c excess_ALSI_return
TSBeta((!month+506)-(!smplstart-1)) = c(2)               '2nd coefficient
ls mrTopALT c excess_ALSI_return
mlongTSALTBeta((!month+506)-(!smplstart-1)) = c(2)       '2nd coefficient
ls mrBotALT c excess_ALSI_return
mshortTSALTBeta((!month+506)-(!smplstart-1)) = c(2)      '2nd coefficient
ls rtsALT c excess_ALSI_return
TSALTBeta((!month+506)-(!smplstart-1)) = c(2)            '2nd coefficient
next
```

Appendix B: Momentum strategy portfolios

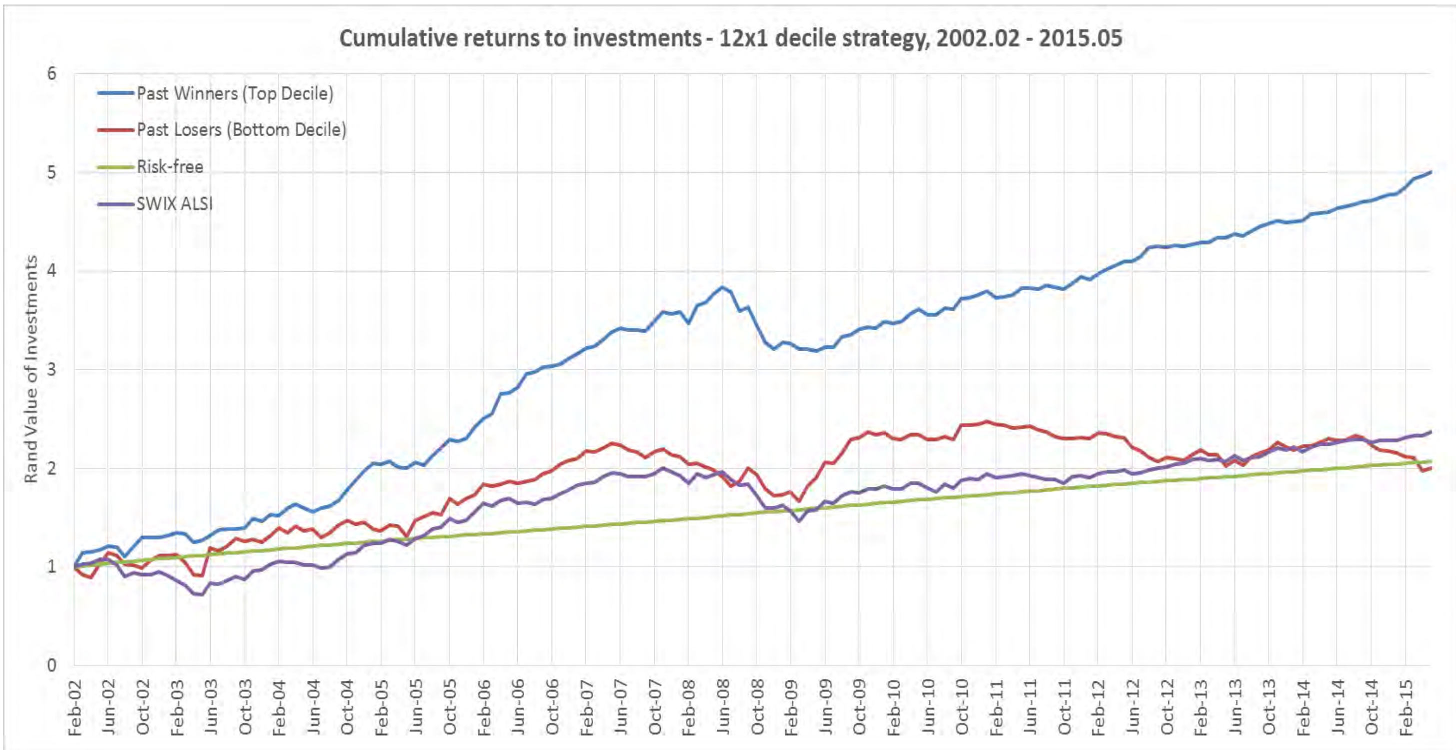
B1: Decile cross-sectional portfolios

This table presents the characteristics of the monthly decile cross-sectional momentum portfolios' excess returns over the period 2002.02-2015.05. The mean excess returns and standard deviations are in percent and annualised, whilst the Sharpe ratio is also annualised. Returns to the "winner minus loser" (WML) portfolio are calculated as according to Equation 1. The cross-sectional momentum strategies are written in the form: (formation period) x (holding period).

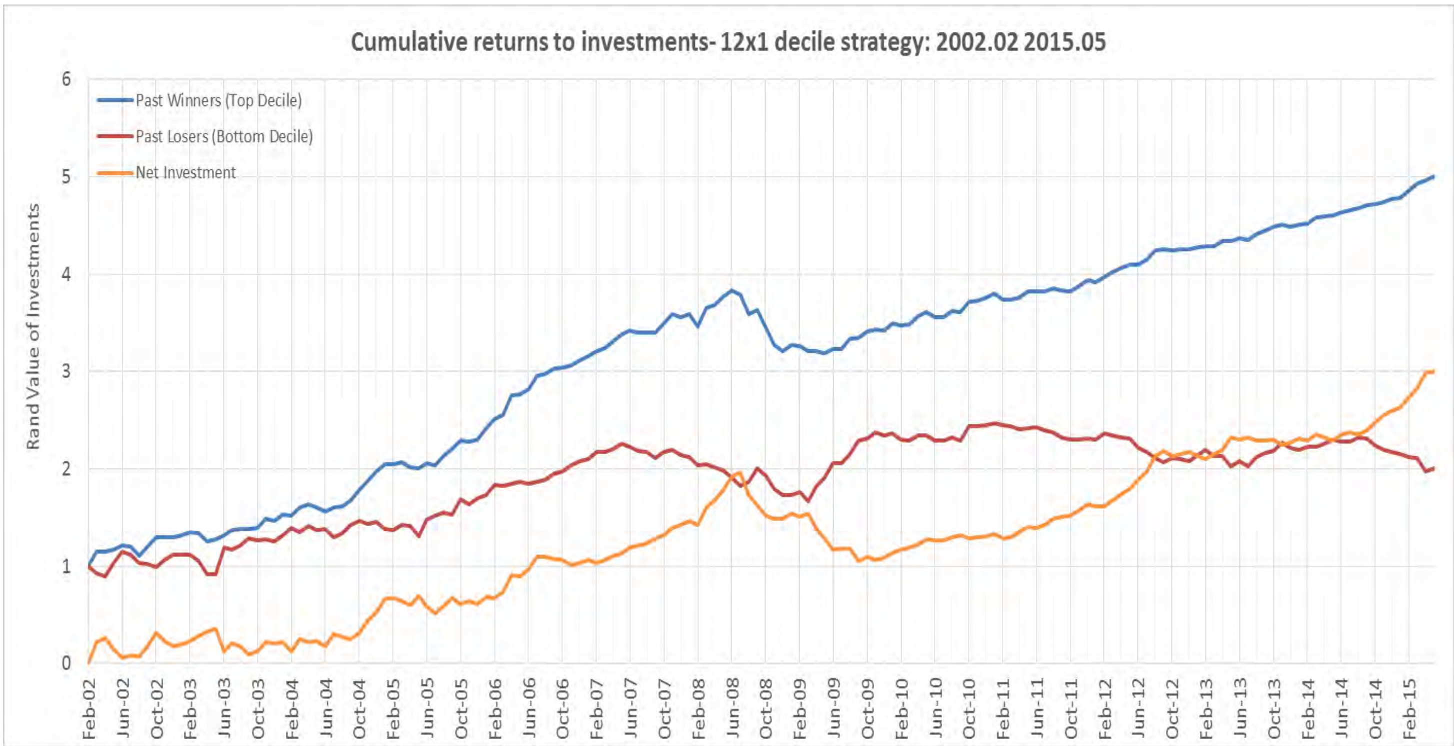
Cross-sectional strategy	1x1	2x1	3x1	4x1	5x1	6x1	12x1	18x1	24x1	36x1	48x1	60x1
Excess return to winner, R_W	12.24	16.22	21.00	24.60	27.33	29.16	30.21	26.41	26.48	24.42	22.27	17.40
Excess return to loser, R_L	21.35	19.93	13.70	12.89	13.21	8.36	7.59	8.01	10.00	7.70	8.47	13.86
Return to WML, R_{WML}	-9.11	-3.71	7.31	11.71	14.12	20.80	22.63	18.40	16.48	16.72	13.79	3.54
T-statistic: $t(R_{WML})$	-1.60	-0.61	1.22	1.94	2.23	3.17	3.39	2.88	2.64	2.64	2.36	0.64
Standard deviation, σ_{WML}	20.72	22.09	21.87	22.02	23.09	23.99	24.35	23.37	22.77	23.16	21.38	20.22
Skew, SK_{WML}	0.53	0.30	0.07	-0.31	-0.21	-0.14	-0.41	-0.17	-0.13	-0.04	0.25	0.14
Sharpe ratio, SR_{WML}	-0.44	-0.17	0.33	0.53	0.61	0.87	0.93	0.79	0.72	0.72	0.65	0.18

B1I: DECILE 12X1 CROSS-SECTIONAL PORTFOLIOS

This figure plots the cumulative returns over the period 2002.02-2015.05 for four key investments: the 12x1 top decile "past winner" portfolio, the 12x1 bottom decile "past loser" portfolio, the risk-free asset, and the benchmark – the Shareholder-weighted All-Share Index (SWIX ALSI). This plot assumes a R1 investment in each of the four assets over each month, beginning in February 2002. With the exception of the risk-free asset, investments' returns are presented net of the risk-free rate of return.

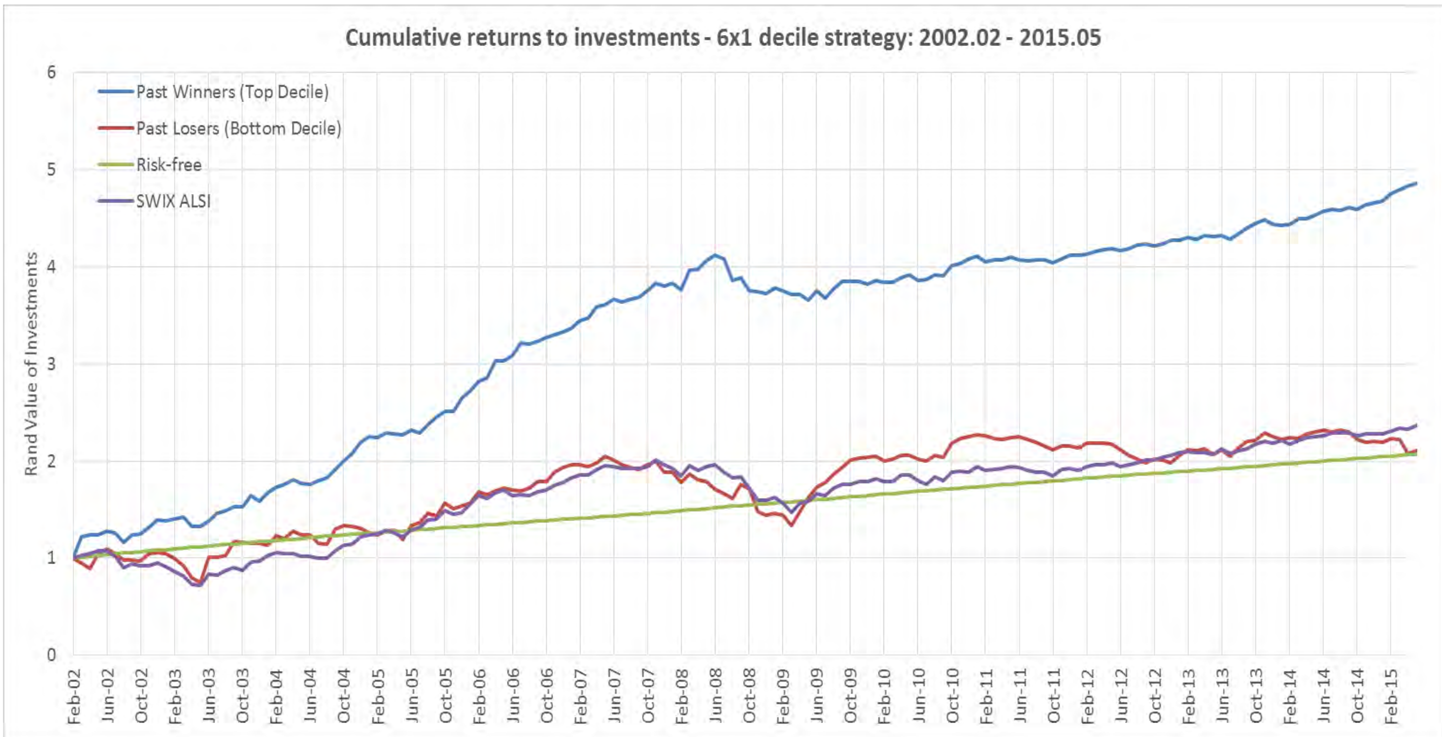


This figure plots the cumulative returns over the period 2002.02-2015.05 for the 12x1 top decile “past winner” portfolio, the 12x1 bottom decile “past loser” portfolio and the net investment-neutral ‘winner minus loser’ (net investment) portfolio. This plot assumes a R1 investment in the “past winner” and “past loser” portfolios over each month, beginning in February 2002. Both the top decile’s and bottom decile’s returns are presented net of the risk-free rate of return.

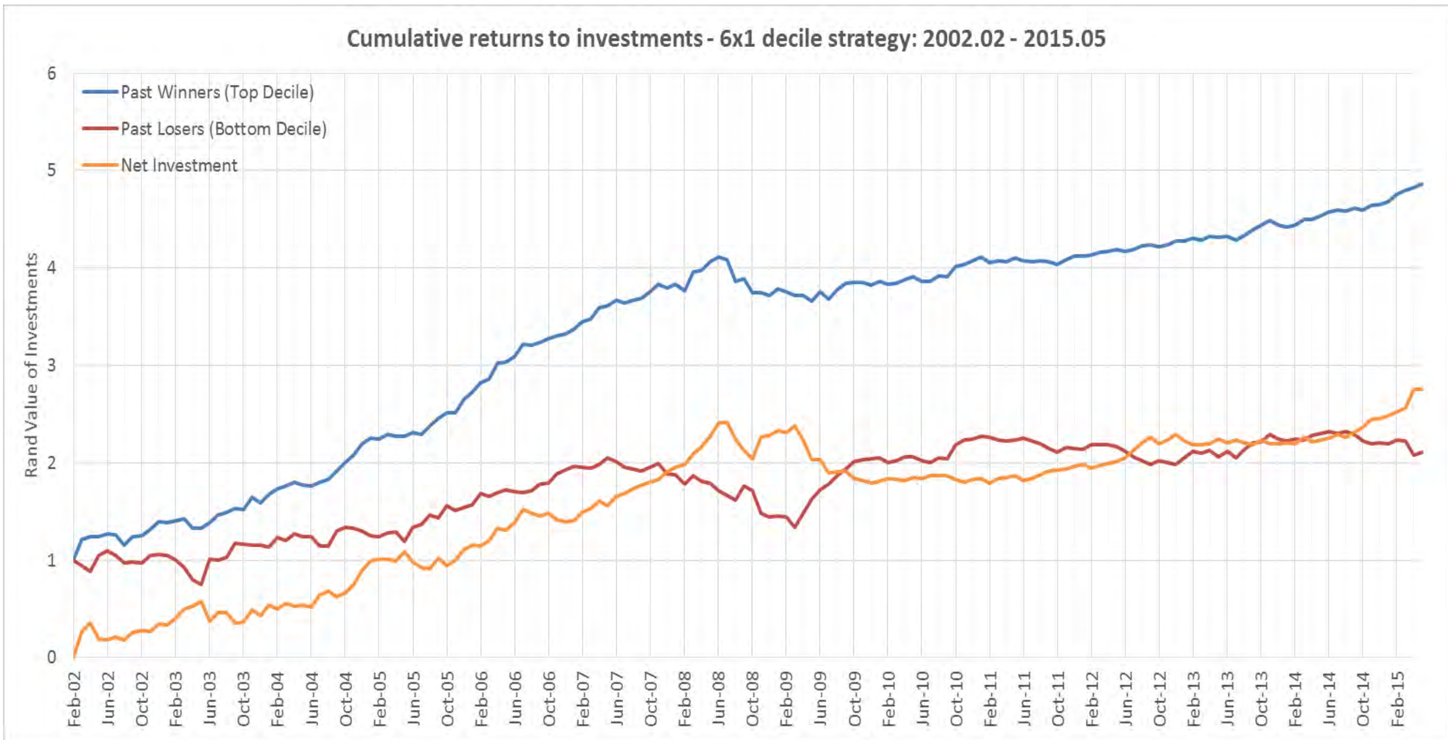


B1ii: Decile 6x1 cross-sectional portfolios

This figure plots the cumulative returns over the period 2002.02-2015.05 for four key investments: the 6x1 top decile "past winner" portfolio, the 6x1 bottom decile "past loser" portfolio, the risk-free asset, and the benchmark – the Shareholder-weighted All-Share Index (SWIX ALSI). This plot assumes a R1 investment in each of the four assets over each month, beginning in February 2002. With the exception of the risk-free asset, investments' returns are presented net of the risk-free rate of return.

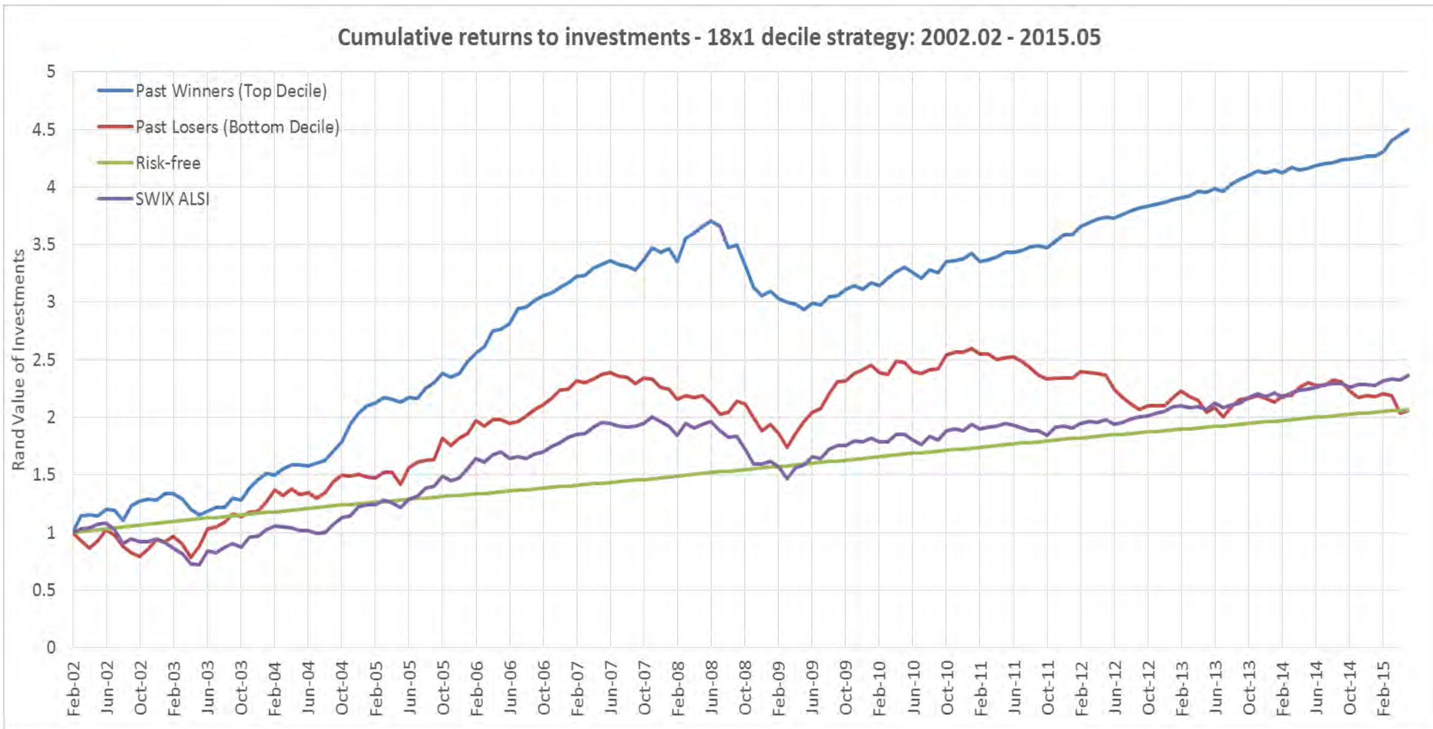


This figure plots the cumulative returns over the period 2002.02-2015.05 for the 6x1 top decile "past winner" portfolio, the 6x1 bottom decile "past loser" portfolio and the net investment-neutral 'winner minus loser' (net investment) portfolio. This plot assumes a R1 investment in the "past winner" and "past loser" portfolios over each month, beginning in February 2002. Both the top decile's and bottom decile's returns are presented net of the risk-free rate of return.

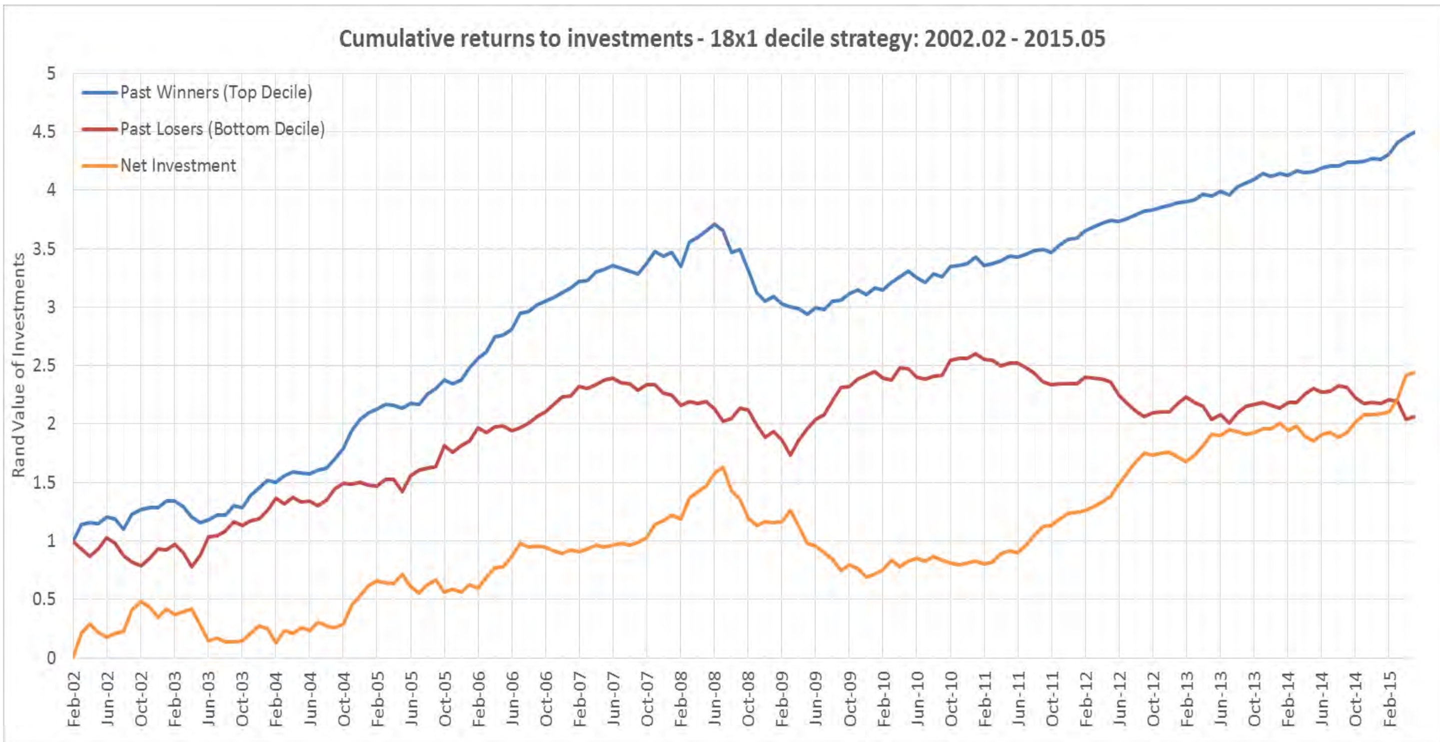


B1III: DECILE 18X1 CROSS-SECTIONAL PORTFOLIOS

This figure plots the cumulative returns over the period 2002.02-2015.05 for four key investments: the 18x1 top decile "past winner" portfolio, the 18x1 bottom decile "past loser" portfolio, the risk-free asset, and the benchmark – the Shareholder-weighted All-Share Index (SWIX ALSI). This plot assumes a R1 investment in each of the four assets over each month, beginning in February 2002. With the exception of the risk-free asset, investments' returns are presented net of the risk-free rate of return.



This figure plots the cumulative returns over the period 2002.02-2015.05 for the 18x1 top decile “past winner” portfolio, the 18x1 bottom decile “past loser” portfolio and the net investment-neutral ‘winner minus loser’ (net investment) portfolio. This plot assumes a R1 investment in the “past winner” and “past loser” portfolios over each month, beginning in February 2002. Both the top decile’s and bottom decile’s returns are presented net of the risk-free rate of return.



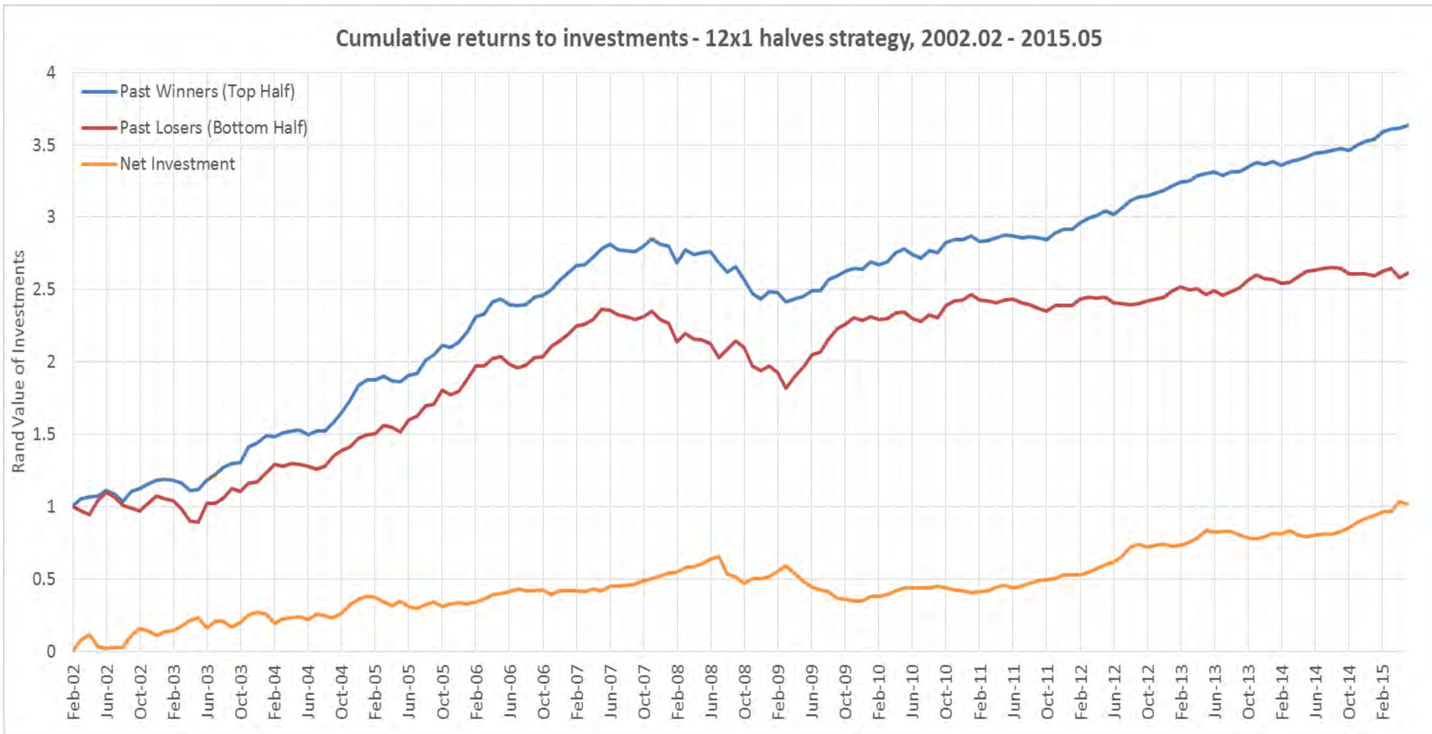
B2: HALVES CROSS-SECTIONAL PORTFOLIOS

This table presents the characteristics of the monthly top half minus bottom half cross-sectional momentum portfolios' excess returns over the period 2002.02-2015.05. The mean excess returns and standard deviations are in percent and annualised, whilst the Sharpe ratio is also annualised. Returns to the "winner minus loser" (WML) portfolio are calculated as according to Equation 1. The cross-sectional momentum strategies are written in the form: (formation period) x (holding period).

Cross-sectional strategy	1x1	2x1	3x1	4x1	5x1	6x1	12x1	18x1	24x1	36x1	48x1	60x1
Excess return to winner, R_W	14.19	15.71	15.65	17.80	17.62	18.68	19.89	20.26	19.70	17.82	18.26	17.79
Excess return to loser, R_L	18.15	16.79	16.71	14.59	14.69	13.52	12.20	11.99	12.33	13.83	13.34	13.75
Return to WML, R_{WML}	-3.96	-1.08	-1.06	3.21	2.93	5.16	7.69	8.26	7.37	3.99	4.93	4.03
T-statistic: $t(R_{WML})$	-1.82	-0.41	-0.39	1.25	1.15	1.99	2.84	3.02	2.66	1.44	1.92	1.65
Standard deviation, σ_{WML}	7.95	9.52	9.87	9.35	9.34	9.47	9.89	9.99	10.13	10.12	9.39	8.92
Skew, SK_{WML}	0.09	-0.21	-0.57	-0.52	-0.78	-0.71	-0.72	-0.61	-0.71	-0.52	-0.48	0.01
Sharpe ratio, SR_{WML}	-0.50	-0.11	-0.11	0.34	0.31	0.54	0.78	0.83	0.73	0.39	0.52	0.45

B2I: HALVES 12X1 CROSS-SECTIONAL PORTFOLIOS

This figure plots the cumulative returns over the period 2002.02-2015.05 for the 12x1 top half "past winner" portfolio, the 12x1 bottom half "past loser" portfolio and the net investment-neutral 'winner minus loser' (net investment) portfolio. This plot assumes a R1 investment in the "past winner" and "past loser" portfolios over each month, beginning in February 2002. Both the top half's and bottom half's returns are presented net of the risk-free rate of return.



B3: Time-series portfolios

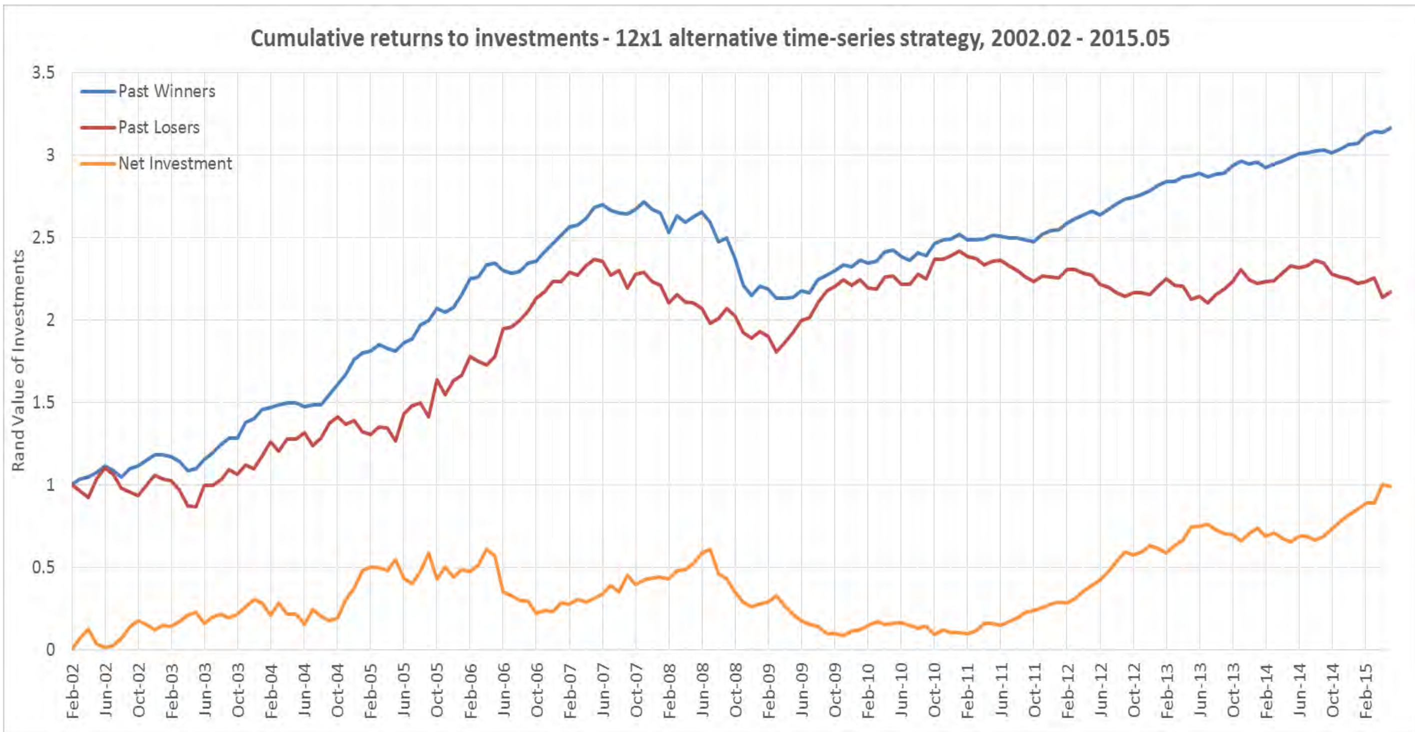
This table presents the characteristics of the monthly time-series momentum portfolios' excess returns over the period 2002.02-2015.05. Panel A presents the first three moments of the investment-neutral approach (Eq. 3), while Panel B presents the same moments from the non-zero net investment approach (Eq. 4). The mean excess returns and standard deviations are in percent and annualised, whilst the Sharpe ratio is also annualised. The time-series momentum strategies are written in the form: (formation period) x (holding period).

Panel A	**1x1**	**2x1**	**3x1**	**4x1**	**5x1**	**6x1**	**12x1**	**18x1**	**24x1**	**36x1**	**48x1**	**60x1**
Excess return to winner, R_W	15.99	16.97	16.97	18.26	17.80	17.40	16.33	15.30	17.21	16.77	17.05	16.44
Excess return to loser, R_L	17.54	16.06	12.02	9.41	10.26	7.29	8.89	8.90	9.62	7.76	8.97	12.43
Return to WML, R_{WML}	-1.55	0.91	4.95	8.85	7.53	10.11	7.44	6.40	7.59	9.01	8.08	4.02
T-statistic: $t(R_{WML})$	3.57	4.38	4.51	4.74	4.63	5.46	5.51	4.07	4.59	5.15	4.73	4.14
Standard deviation, σ_{WML}	10.49	12.08	11.62	11.55	13.16	14.52	17.02	16.82	16.70	19.30	22.39	20.40
Skew, SK_{WML}	-0.13	-0.27	-0.32	-0.32	-0.56	-0.54	-0.89	-0.47	-0.39	-0.22	1.04	1.37
Sharpe ratio, SR_{WML}	-0.15	0.08	0.43	0.77	0.57	0.70	0.44	0.38	0.45	0.47	0.36	0.20

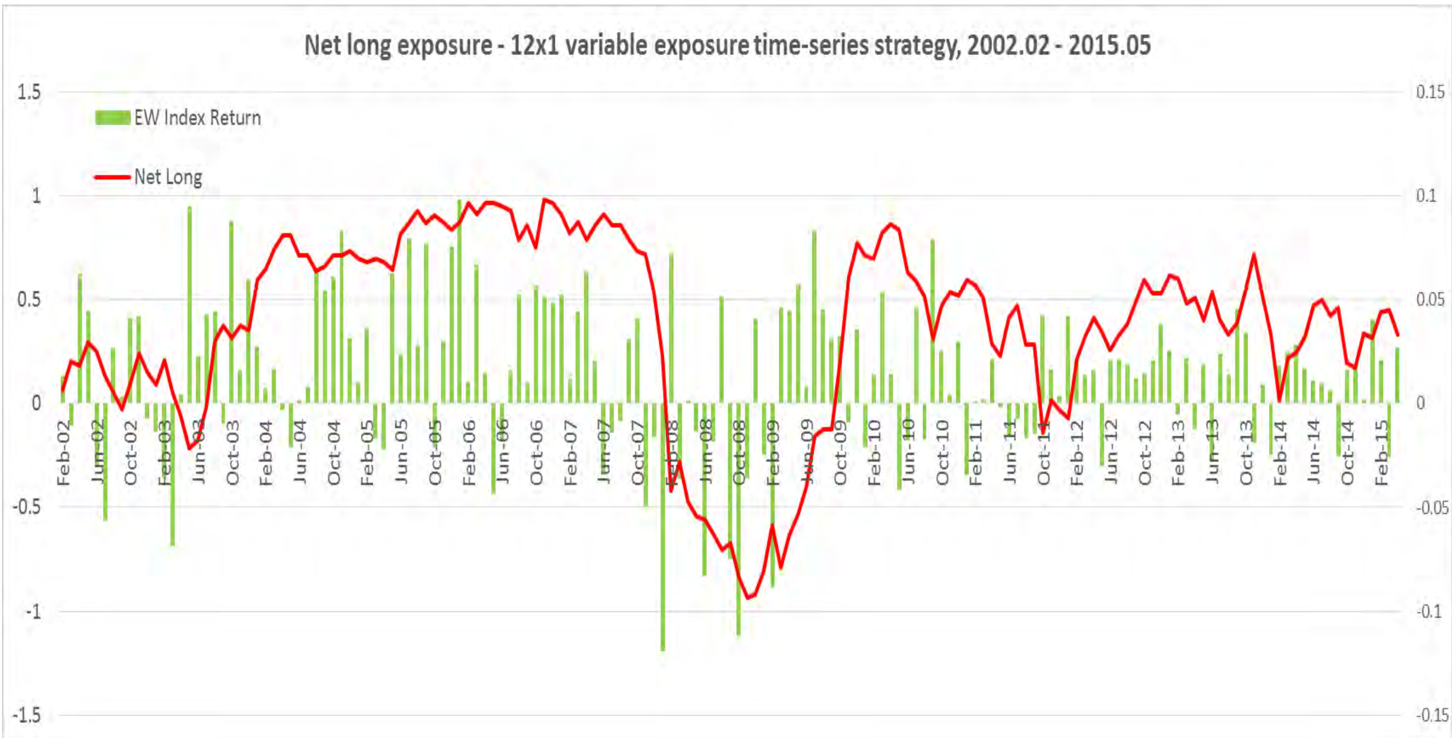
Panel B	**1x1**	**2x1**	**3x1**	**4x1**	**5x1**	**6x1**	**12x1**	**18x1**	**24x1**	**36x1**	**48x1**	**60x1**
Return to TS, R_{TS}	13.37	18.21	20.44	22.00	22.20	25.47	28.09	22.44	24.28	27.09	28.19	25.02
T-statistic: $t(R_{TS})$	3.57	4.38	4.51	4.74	4.63	5.46	5.51	4.07	4.59	5.15	4.73	4.14
Standard deviation, σ_{TS}	13.66	15.18	16.56	16.95	17.49	17.05	18.60	20.15	19.31	19.19	21.74	22.06
Skew, SK_{TS}	0.67	0.29	-0.03	0.25	0.34	0.49	0.05	-0.24	-0.33	-0.78	-0.82	-0.62
Sharpe ratio, SR_{TS}	0.98	1.20	1.23	1.30	1.27	1.49	1.51	1.11	1.26	1.41	1.30	1.13

B3I: 12X1 TIME-SERIES PORTFOLIO

This figure plots the cumulative returns over the period 2002.02-2015.05 for the 12x1 "past winner" portfolio, the 12x1 "past loser" portfolio and the net investment-neutral 'winner minus loser' (net investment) portfolio. This plot assumes a R1 investment in the "past winner" and "past loser" portfolios over each month, beginning in February 2002. Both the long and short returns are presented net of the risk-free rate of return.

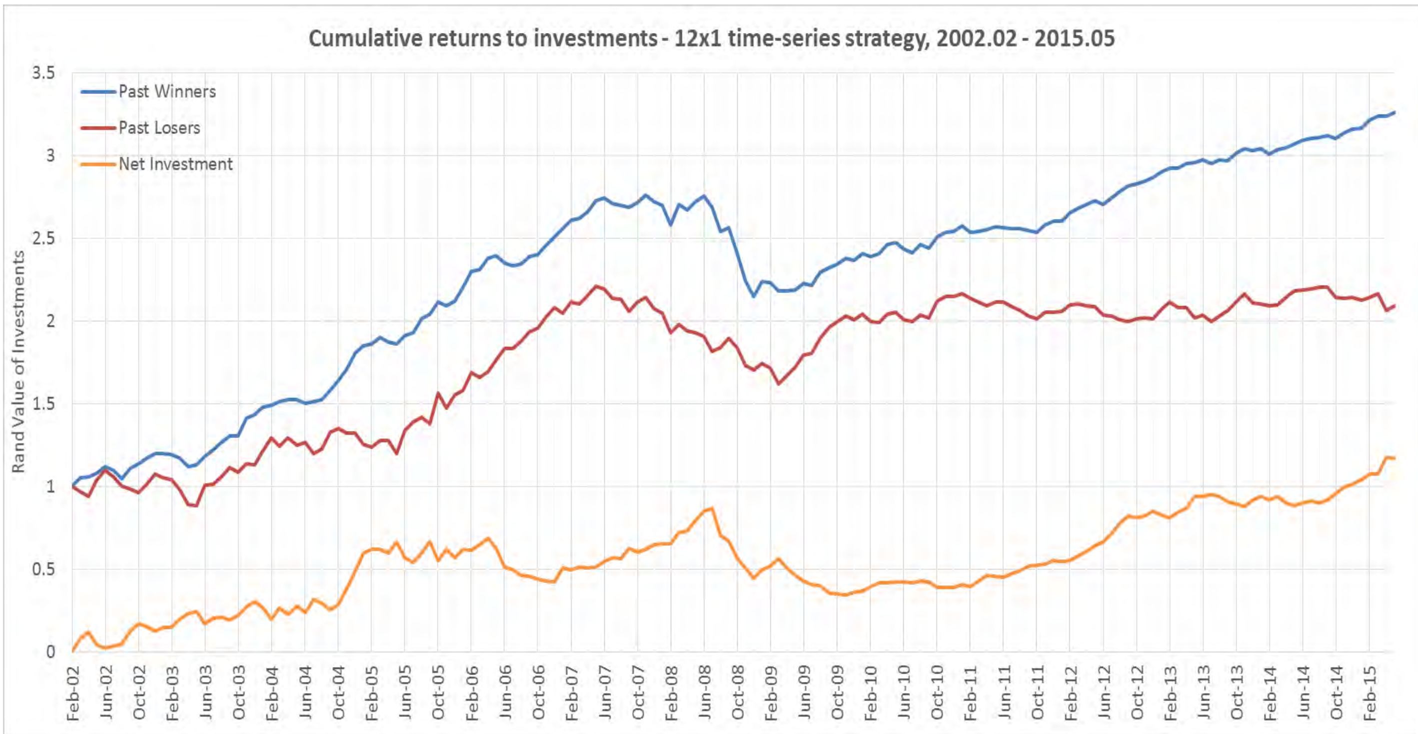


This figure plots the 12x1 variable net investment exposure time-series (TS NE=variable) strategy's monthly net long exposure to the market against the monthly excess return to the equally-weighted index (EW Index). The net long and EW Index returns are both in percent.

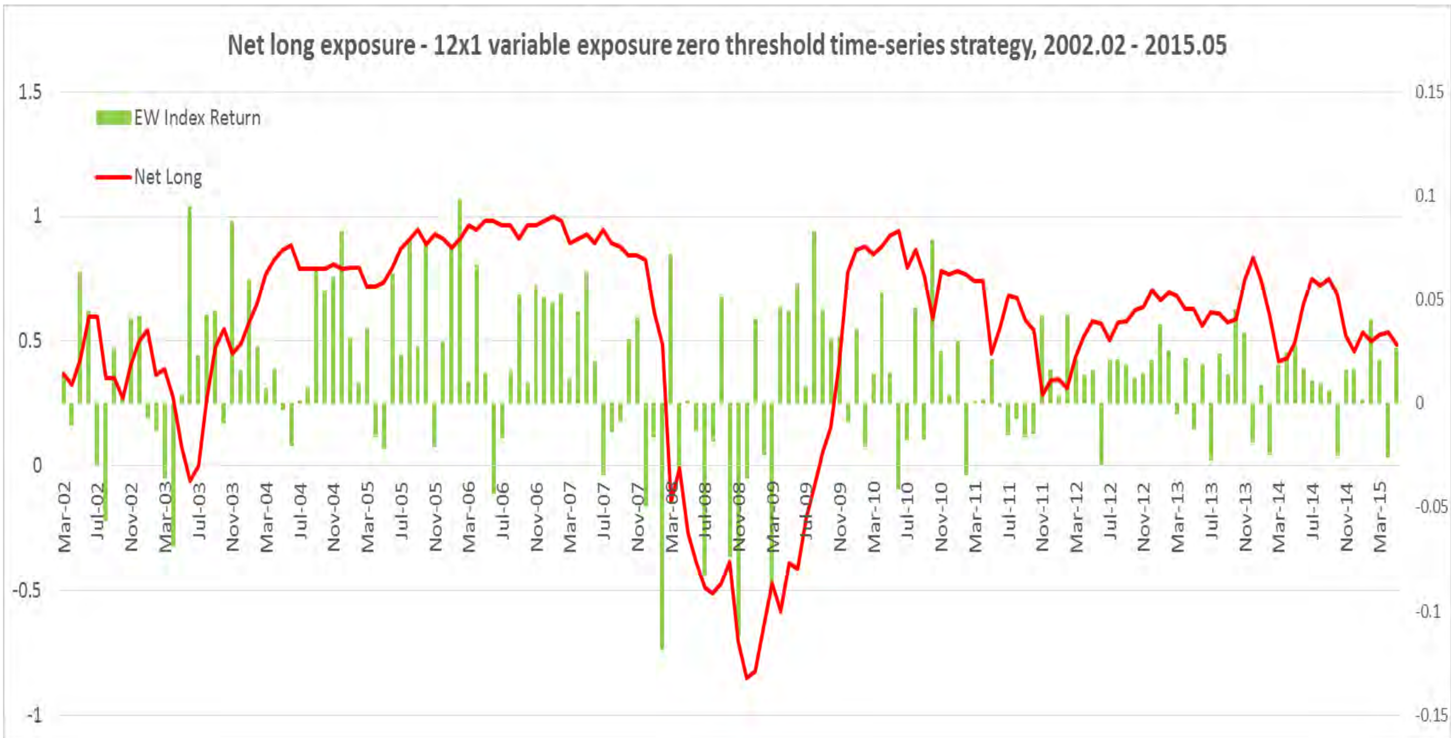


B3II: 12X1 ZERO ABSOLUTE THRESHOLD TIME-SERIES PORTFOLIO (TSALT)

This figure plots the cumulative returns over the period 2002.02-2015.05 for the 12x1 zero absolute return threshold time-series “past winner” portfolio, 12x1 zero absolute threshold “past loser” portfolio and the net investment-neutral ‘winner minus loser’ (net investment) portfolio. This plot assumes a R1 investment in the “past winner” and “past loser” portfolios over each month, beginning in February 2002. Both the long and short returns are presented net of the risk-free rate of return.

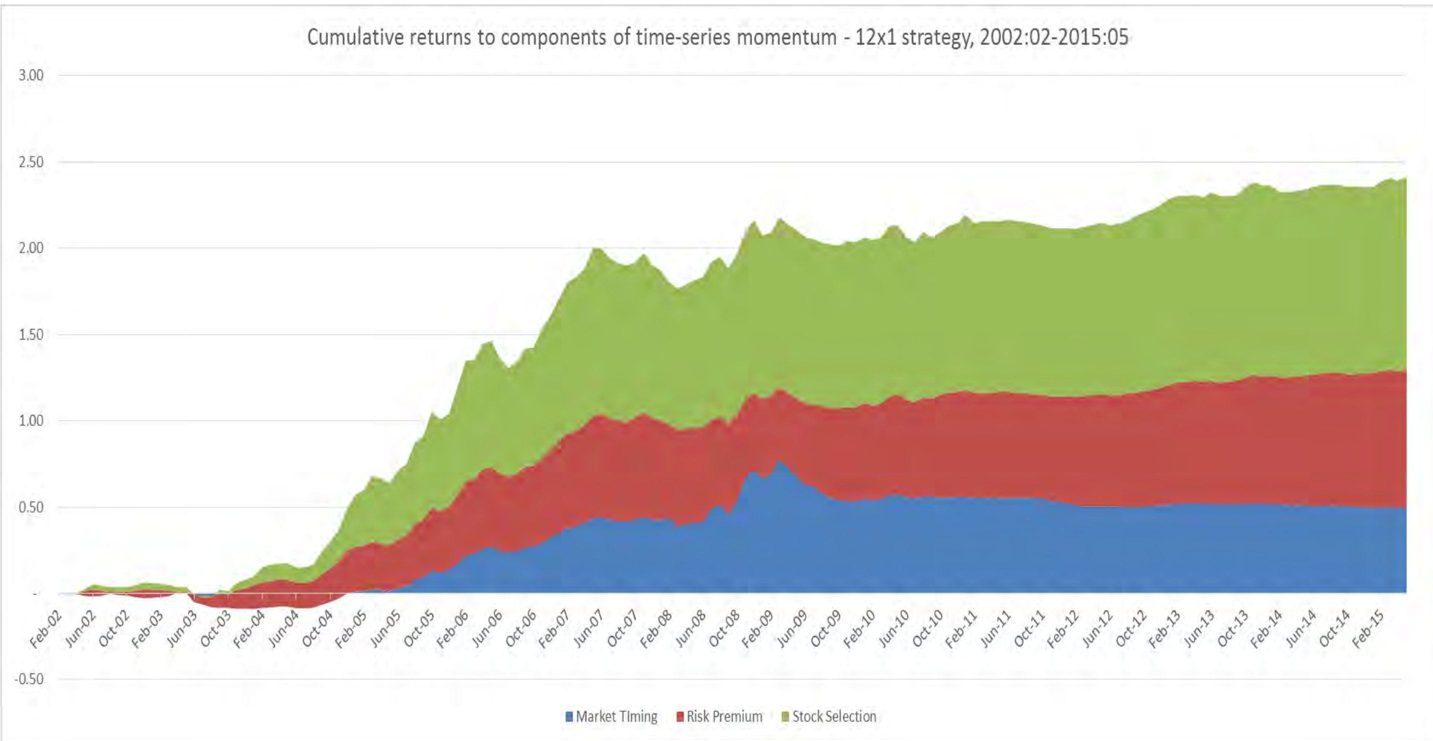


This figure plots the 12x1 variable net investment exposure zero returns threshold time-series (TSAlt NE=variable) strategy's monthly net long exposure to the market against the monthly excess return to the equally-weighted index (EW Index). The net long and EW Index returns are both in percent.



Appendix C: Cumulative components of time-series momentum

This figure plots the cumulative returns to the components of time-series momentum for the 12x1 variable exposure strategy, over the period 2002.02-2015.05. The risk premium component is calculated monthly by Eq. 5 and the market timing component by Eq. 6. The stock selection component is observed by the remainder of the difference between the 12x1 time-series and top half minus bottom half cross-sectional approach.



Appendix D: t-statistics of intercept term of time-series and cross-sectional regressions

This table presents the t-statistics of the pooled regressions of time-series (TS) momentum strategies' returns with the corresponding cross-sectional momentum strategies' returns over the period 2002.02-2015.05. Both the top decile minus bottom decile (CS deciles) and the top half minus bottom half (CS halves) cross-sectional methods have been accounted for in the regressions. The cross-sectional momentum strategies are written in the form: (formation period) x (holding period).

	1x1	2x1	3x1	4x1	5x1	6x1	12x1	18x1	24x1	36x1	48x1	60x1
TS (independent) CS deciles (dependent)	-3.16	-2.39	-0.83	-0.45	-0.09	0.54	1.07	1.30	1.09	1.10	0.97	-0.27
TS (independent) CS halves (dependent)	-3.80	-2.28	-2.49	-1.24	-1.49	-1.07	0.20	1.18	0.85	-0.30	0.47	0.68
CS deciles (independent) TS (dependent)	3.72	4.41	3.68	3.43	3.09	3.62	3.99	2.58	2.65	2.88	3.06	3.60
CS halves (independent) TS (dependent)	4.20	4.37	4.58	3.94	3.98	4.52	4.27	2.48	2.63	3.42	3.22	3.68

Appendix E: Momentum crashes

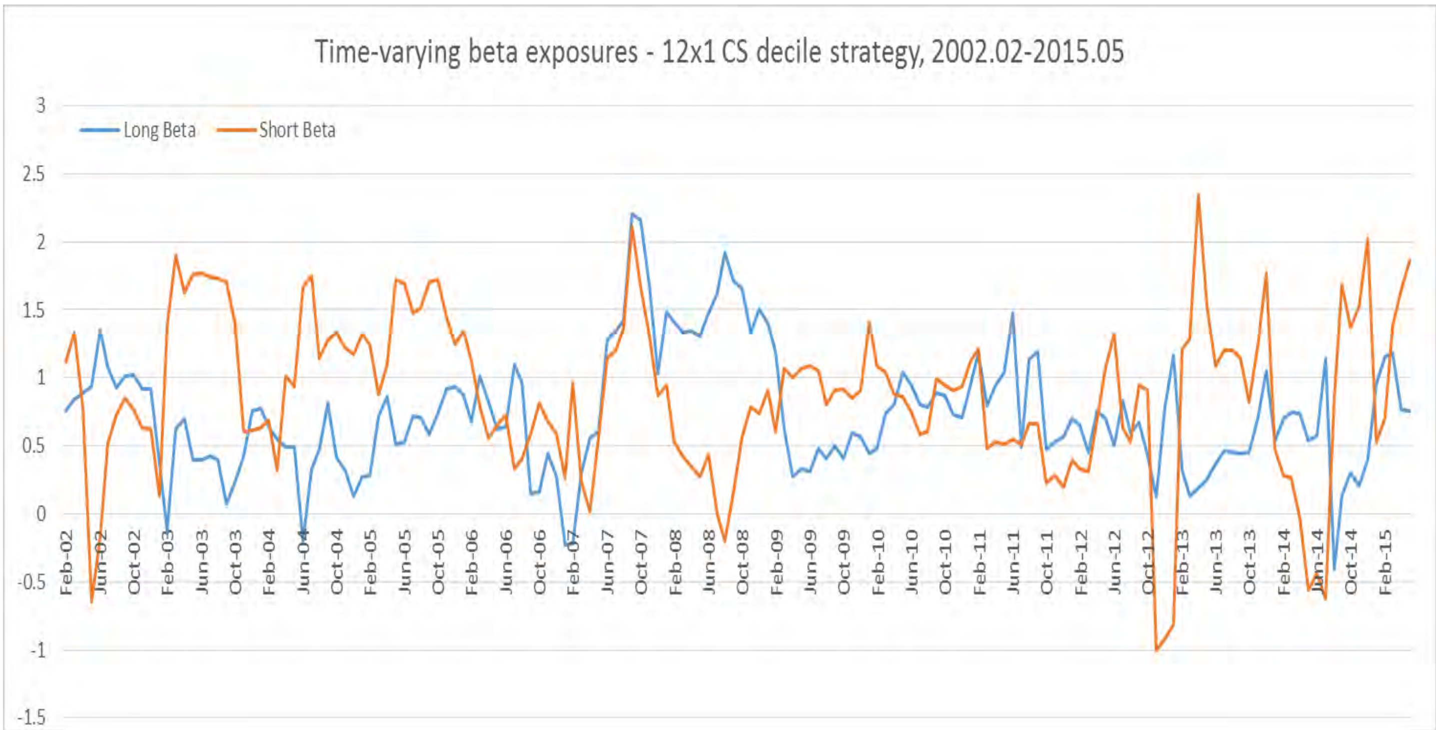
E1: Skewness

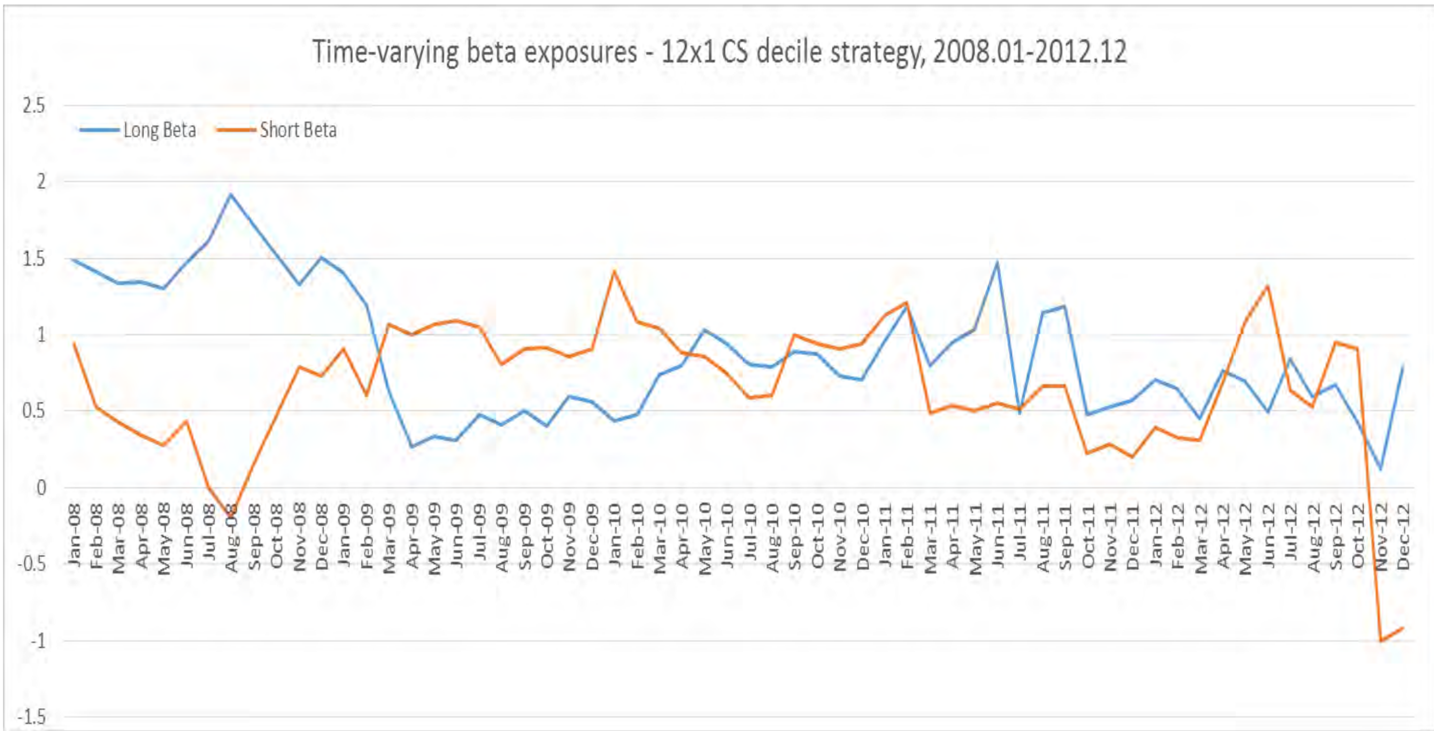
This table presents the realised skewness of returns of each of the momentum strategies previously examined in this report: the top decile minus bottom decile cross-sectional strategy (CS deciles), the top half minus bottom half cross-sectional strategy (CS halves), the investment-neutral time-series strategy (TS NE=0), the variable exposure time-series strategy (TS NE=variable), the zero threshold investment-neutral time-series strategy (TSAlt NE=0) and the zero threshold variable exposure time-series strategy (TSAlt NE=variable). All strategies' skewness is presented over the period 2002.02-2015.05. Significant negative (positive) skewness exists when the strategy's skewness is lower (higher) than -0.3849 (0.3849).

	1x1	2x1	3x1	4x1	5x1	6x1	12x1	18x1	24x1	36x1	48x1	60x1
CS deciles	0.53	0.30	0.07	-0.31	-0.21	-0.14	-0.41	-0.17	-0.13	-0.04	0.25	0.14
CS halves	0.09	-0.21	-0.57	-0.52	-0.78	-0.71	-0.72	-0.61	-0.71	-0.52	-0.48	0.01
TS NE=0	-0.12	0.04	-0.32	-0.34	-0.74	-0.88	-0.57	-0.62	-0.20	0.01	0.29	0.23
TS NE=variable	0.69	0.24	-0.21	0.19	0.31	0.53	0.26	-0.16	-0.27	-0.46	-0.97	-0.83
TSAlt NE=0	-0.13	-0.27	-0.32	-0.32	-0.56	-0.54	-0.89	-0.47	-0.39	-0.22	1.04	1.37
TSAlt NE=variable	0.67	0.29	-0.03	0.25	0.34	0.49	0.05	-0.24	-0.33	-0.78	-0.82	-0.62

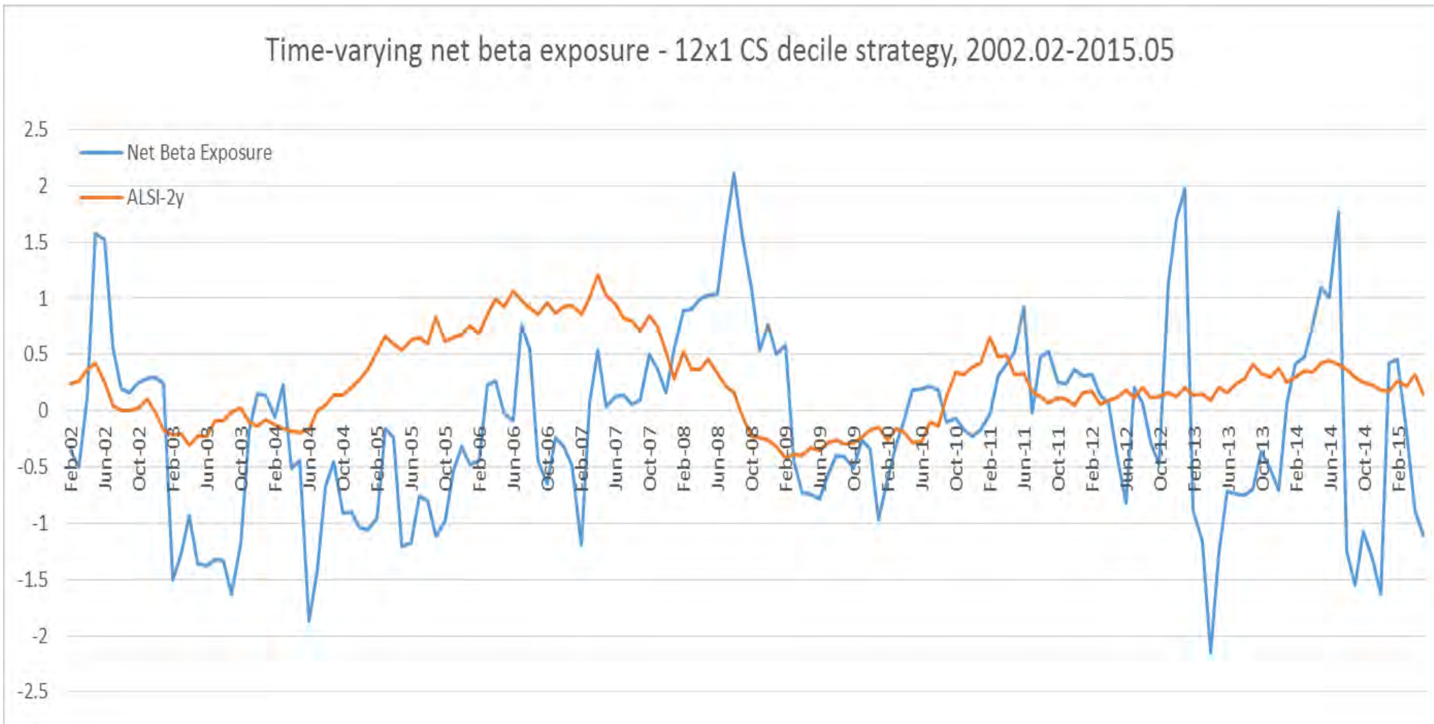
E2: TIME-VARYING BETA EXPOSURES

This figure plots the estimated market beta exposures to South Africa's All-Share Index (ALSI) of the 12x1 top decile cross-sectional long "past winner" portfolio and 12x1 bottom decile cross-sectional short "past loser" portfolio over the period 2002.02-2015.05 and sub-period 2008.01-2012.12. The betas were estimated using a 6-month rolling regression of the excess returns to the portfolios against the excess returns on the ALSI.





This figure plots the net estimated market beta exposure to South Africa's All-Share Index (ALSI) of the 12x1 top decile cross-sectional long "past winner" portfolio and 12x1 bottom decile cross-sectional short "past loser" portfolio over the period 2002.02-2015.05. With reference to Daniel and Moskowitz's (2013) work, the lagged 2-year market return is also presented.



E3: Months with momentum losses exceeding 10%

This table presents the long and short returns to the strategy in the months in which any one of the 12x1 base-case strategies earned momentum losses exceeding 10%, over the period 2002.02-2015.05. Additionally, over the sub-periods 2008.08-2008.10 (blue) and 2009.04-2009-06 (green) the cumulative returns to each of the strategies are calculated. Cells highlighted in red refer to momentum crash scenarios (i.e. significant losses (10% p.m.) earned on an extended time basis (minimum 3-months)).

CS Deciles	Long Return	Short Return	Net Return	Cumulative Return	CS Halves	Long Return	Short Return	Net Return	Cumulative Return
May-02	1.87%	13.64%	-11.77%						
Jun-03	4.88%	28.01%	-23.12%						
Jun-05	5.45%	16.52%	-11.07%						
Aug-08	-19.26%	4.19%	-23.46%	-23.46%	Aug-08	-6.46%	5.28%	-11.74%	-11.74%
Sep-08	3.62%	13.66%	-10.04%	-33.49%	Sep-08	3.87%	6.38%		-14.25%
Oct-08	-18.24%	-7.03%	-11.22%	-44.71%	Oct-08	-9.23%	-4.97%		-18.51%
Apr-09	0.09%	14.78%	-14.69%	-14.69%	Apr-09	2.02%	7.69%		
May-09	-1.49%	9.04%	-10.53%	-25.22%	May-09	1.71%	6.91%		
Jun-09	4.11%	15.18%	-11.07%	-36.29%	Jun-09	4.06%	8.55%		
Sep-09	1.74%	13.88%	-12.14%	-48.43%					

TS NE=0	Long Return	Short Return	Net Return	Cumulative Return	TS NE=variable			Return	Cumulative Return
					Jun-03			-11.42%	
Oct-05	7.05%	18.53%	-11.48%						
Jun-06	-4.50%	6.49%	-10.98%						
Aug-08	-14.38%	2.35%	-16.73%	-16.73%	Aug-08				-9.14%
Sep-08	2.28%	5.61%		-20.07%	Sep-08				-18.02%
Oct-08	-15.42%	-5.51%		-29.97%	Oct-08				-13.92%
Apr-09	0.09%	5.36%		-5.27%	Apr-09				-9.59%
May-09	0.47%	5.14%		-9.94%	May-09				-17.81%
Jun-09	3.97%	7.00%		-12.97%	Jun-09				-26.75%

TSAlt NE=0	Long Return	Short Return	Net Return	Cumulative Return	TSAlt NE=variable			Return	Cumulative Return
Jun-05	5.23%	16.52%	-11.29%						
Oct-05	6.93%	22.56%	-15.63%						
Jun-06	-4.49%	17.25%	-21.74%						
					Feb-08			-12.57%	
Aug-08	-11.91%	2.85%	-14.76%	-14.76%	Aug-08			-10.11%	-10.11%
Sep-08	2.56%	6.04%		-18.23%	Sep-08				-17.64%
Oct-08	-12.64%	-4.73%		-26.14%	Oct-08				-18.80%
Apr-09	-0.06%	6.09%		-6.15%	Apr-09				-9.67%
May-09	0.43%	5.97%		-11.69%	May-09				-17.72%
Jun-09	3.71%	7.38%		-15.35%	Jun-09				-25.96%